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Image Transform and Hybrid Optimization Based Feature Reduction for Leaf Diseases Classification

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***Abstract:** In recent years, there has been amazing progress in technology innovation across many sectors, including medical care, homeland security, the arts, and even agriculture. The ability to run one's business well is highly regarded in every sector. Because to recent advancements in technology, such as smart phones and the Internet of Things, this is now a distinct possibility. In this research, we offer a smart management system for horticulture that makes use of machine learning methods. This system is based on the smart management scheme that was previously described. As a component of horticulture management, many academics have advocated for the use of machine learning to analyse plant growth based on the features of the leaf. We used the grayscale image, which employed numerous features for classification while simultaneously normalising the pixel values. As a consequence of this, the processing of damaged leaves in their early stages takes more time and results in less accurate classification. As a result, for the purpose of this work, we do a colour space conversion in order to investigate the image in terms of hue, saturation, and value. Following that, it extracted features from the Value channel by making advantage of the histogram's attributes. After that, the best characteristics were chosen by a process that included both particle swarm and cuckoo search optimisation. Following this, a regression neural network was trained to classify data based on the features that had been selected in the previous step. In order to evaluate how effective the proposed strategy is, classification performance criteria such as accuracy, sensitivity, and specificity were utilised. The suggested approach was tested in a simulated Windows 10 environment using a real-time dataset and the MATLAB software. It was compared to other methods that are already in use. While evaluating performance, comparisons to the current state of the art are conducted with regard to accuracy, sensitivity, and specificity.*
***Keywords:** Smart management, Horticulture, Machine learning, Hybrid, optimization, HSV domain.*

I. INTRODUCTION

India is famous for its agriculture, cultural and heritage structures. Among these, agriculture plays a major role in the Indian economy's growth. But in today's technological development, agricultural growth is in a diminishing stage by converting the agricultural land into industrial or commercial buildings.

The main reasons behind the diminishing agricultural growth are technological development and the younger generation's lack of interest in agriculture. This can be modified by introducing technology advancement in agriculture. This will help the existing old farmer and welcome the young budding farmer into agriculture. For example, introducing smart irrigation systems and crop monitoring using the internet of things and computer-aided technologies.

Based on this smart management technique in agriculture, in this paper, an automated leaf disease classification algorithm was proposed using machine learning algorithms. The proposed algorithms were selected based on analysing various techniques that are used for leaf disease classification. The techniques that are used in identifying the diseased region are discussed below.

Utilized satellite images like multispectral (MS), hyperspectral (HS), and visible images (VI) to identify the diseased beetroot leaves. In combined the features of MS and VI images using a fusion technique. Then, they performed classification using machine learning algorithms called Naive Bayes (NB) and the K-nearest neighbour algorithm (K-NN). While in they utilized a single HS image and a decision tree technique for classification. A multi-level based citrus leaf disease classification was proposed by using the ensemble algorithm Adaboost technique.

Mammography is the most trustworthy technique that is currently available and can save lives by detecting breast cancer in its early stages. Digital mammography is now the most accurate screening tool currently available for breast cancer. In this piece of research, the authors present a strategy that makes use of a multi-SVM classifier for the purpose of finding and classifying breast cancer masses in digital mammograms[2].

An automated method is used to segment the damaged mammogram by first splitting it into smaller parts, and then merging those smaller parts back together again using a region-based segmentation technique.

The starting point of this technique is the selection of a seed location [3]. The proposed algorithm employs a process known as area split and merge to isolate the affected area of a picture from its surrounding pixels and morphological procedures to digitally reduce noise. The image undergoes both of these processes.

The image types and procedures utilized for classification were outlined in the paper [4]. It emphasized the many sorts of image capture ranges, such as visual, thermal, and satellite imaging, in image types. [5] suggested a feature selection method based on the detection of illnesses in rice leaves. The best features from the standard feature set were chosen using a rough set method. For cherry leaves, [6] developed a chemical-oriented virus-affected leaf disease classification. The pathogen characteristics of twisted and rusty leaf varieties were investigated using in vitro and categorized.

The visual qualities of hyperspectral images are described by a number of bands. Only a few of the many bands had access to the crucial information. In such situations, band selection is critical. A sequential projection was used in [4] to suggest a band selection method. The suggested method was tested using HS tomato images, which were categorised using an extreme machine learning algorithm. The suggested pre-processing and feature extraction strategies in the majority of the publications were for leaf disease classification. They suggested a beet leaf categorization based on post-processing in [10].

A study of alternative methodologies for classifying Alfalfa leaf diseases was conducted. For lesion segmentation, a combination of K-median clustering and linear discriminate analysis works well [11]. The production of tan in leaves is investigated using sorghum pigment analysis, which is based on gene missing and translated components [12].

For automated leaf disease classification, a histogram-based feature extraction using colour-transformed leaf images was proposed in [13]. Similarly, utilizing ensemble voting and histogram matching approaches, the histogram properties of soybean leaves were utilized to diagnose the leaf disease in [14]. The methodologies utilized to identify leaf diseases using visible range-based images were primarily detailed in the paper [15].

A multi-level processing of cucumber leaf diseases classification was proposed in [16]. Here, they segmented the leaves using K-means, then sparse classification was performed on the texture features from the leaves. Similarly, in [17] also performed the lesion segmentation and SVM-based diseases identification in Cucumber leaves.

The articles [18–19] highlighted the techniques used for identifying the diseases in wheat leaves. In [18], the HS image was processed using spectral indices for classification. In [19], deep learning algorithms were analysed in wheat leaf disease classification. The NB algorithm was used to classify the okra and bitter gourd leaf in [20]. The other recent techniques that were utilized for leaf disease classification are highlighted in the following section.

II. RECENT WORKS

This section is to describe the recent methods that are used for the classification were discussed.

G. R. Jothilakshmi et al., (2017) approach for extracting the region of interest from sono-mammogram pictures based on the detection of unique blocks was proposed. Here, a region expanding technique was used to isolate the afflicted area, and then features were extracted from that area. Then, a radial basis neural network was used for classification after bacterial optimisation was used to pick relevant characteristics. This method's weakness is that it only looked at fungal illnesses.

Iqbal et al. (2018) investigated the detection of citrus leaf diseases. The colour and shape were found to be the best for feature extraction during the analysis. Fuzzy logic was utilized to reduce the number of features. Traditional machine learning techniques were utilized for classification, and classification measures were used to analyse the results. Because there are so many different reduction approaches, the analysis in the feature reduction section was modest.

Liu et al., (2018) proposed a deep learning algorithm for classifying the apple leaf diseases using hyperspectral images. the performance can be enhanced further by using band selection algorithm and different network instead of Alexnet.

Lu et al., (2018) In addition, we used a multispectral satellite image of tomatoes to perform the classification. In this case, principal component analysis was employed to simplify the vegetation indices used for feature extraction. Then, it was categorised using K NN, which is the method of choice when trying to determine which leaves are in good condition.

Barbedo (2018) performed a deep learning-based leaf diseases classification for twelve plant using convolution neural network. The shortcomings of this approach are that it performed the classification on diseases segmented region only.

Lin et al., (2019) also utilized the deep learning algorithm with modification in CNN layers for classifying the wheat diseases. The shortcoming of this approach is it utilized same data for training and it results in over fitting of the network.

Geetharani and pandiyan (2019) also modified the CNN layers and utilized augmentation process for classifying the thirty-nine types of diseases affected leaves. The epoch and batch normalization values were selected using manual approach.

Priyadarshini et al., (2019) modified the Le deep learning network for maize leaf diseases classification. It performed classification only on 3 types only with higher processing time and steps.

III. PAPER CONTRIBUTION

From the analysis of recent techniques and existing algorithms, the following points were observed.
1) For ML algorithms, the images were transformed to grey scale domain.
2) Most of the algorithms utilized segmentation-based classification.
3) The feature selection was using traditional algorithms like PCA, relief algorithm and correlation properties.
4) Deep learning techniques skipped the local features from the images.

Based on the shortcomings, in the existing paper, the moth flame-based Regression neural network was proposed for leaf diseases classification. In that also, the image was processed in grey scale domain. This results in limited classification. Hence to overcome this, in this paper, the following modifications were performed to enhance the diseases identification in leaves.
The modifications of the existing algorithm in this paper are as follows:
- In the pre-processing step, the RGB image is transformed into HSV image instead of grey scale image.
- Because in HSV image, the colour values of the image were preserved in value values.
- The feature extraction was performed on the Value channel of the image.
- In feature reduction part, the hybrid Particle swarm and cuckoo search-based optimization was used.
- The classification is performed through the same Generalized regression neural network.

The brief explanation of proposed Image transform and hybrid optimization technique was given below.

IV. PROPOSED METHOD

This study provided an image transform and hybrid optimization-based feature selection strategy for disease identification in leaves. The final classification was done using a regression neural network. All of the stages above were completed on nine distinct varieties of leaves. The suggested approach's procedure is depicted in Figure 1.

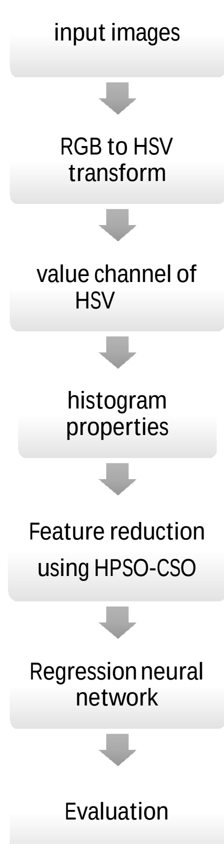

Figure 1. Leaf diseases classification using HPSO-CSO

The steps in the figure 1 are listed below to perform the leaf diseases identification using proposed approach.

Step 1 Healthy and unhealthy images of nine types of leaves were loaded.
Step 2 Resize the images to [256 256]
Step 3 Convert the resized RGB image to HSV image
Step 4 Extract the Value component from HSV image
Step 5 Perform feature extraction on Value component using histogram values.
Step 6 Perform first stage of feature reduction using particle swarm algorithm using following steps
Step 7 Initialize swarm values, iterations and boundary values for PSO
Step 8 Begin PSO by evaluating fitness function
Step 9 After first iteration, update swarm position and velocity for further iterations.
Step 10 Similarly, update the fitness function values.
Step 11 If PSO complete all iterations or conditions reached
Step 12 The top five features were obtained from PSO.
Step 13 This features were reduced using Cuckoo search algorithm to select top two features
Step 14 The CSO also repeat the steps 7 to 12 using its initialization and position update equations.
Step 15 Once all conditions satisfied, the CSO selects top two features for classification.
Step 16 Finally, selected features were used for classification using regression neural network.
Step 17 The classification was performed on 30% of selected features. The remaining features were used for training part.
Step 18 The proposed method performance evaluated using classification performance metrics.

A. Kaggle Dataset

The proposed method's input is derived from the Kaggle plant disease dataset [36]. Table 1 shows the nine leaf classifications that are considered here. There are 30 healthy leaves in each leaf class, while the rest leaves are diseased. Table 1 shows the leaf classes and the number of photos in each class.

Table 1.Leaf distribution in dataset

Type of leaves	Total no of images
Apple	120
Cherry	60
Corn	90
Grapes	120
Peach	60
Pepper bell	60
Potato	90
Strawberry	60
Tomato	300

For processing, a maximum of 990 images are taken. These images were subjected to the remaining steps of the proposed method.

B. Pre-processing

Image resizing and transformation are done on the given dataset. Because the input images are noise-free and the regression neural network can comprehend noisy data, this approach does not require any filtering.

1) Image transformation

First, the image is resized to a standard size into 256 * 256 for easy processing. Then, the resized image was subjected to image transformation technique. Here, the RGB channel of image is transformed into HSV channel. Because in HSV the colour values are preserved better as compared to the grey scale transformation. The steps in RGB to hsv is shown in the below equations.

Step 1 Calculate R’, G’ and B’ from RGB using equation 1 to 3.

$$R' = R/255 \qquad (1)$$

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$$G' = G/255 \quad (2)$$
$$B' = B/255 \quad (3)$$

Step 2 Calculate the maximum and minimum value for the transformed RGB using equations 4 and 5.

$$cmax = \max(R', G', B') \quad (4)$$
$$cmin = \min(R', G', B') \quad (5)$$

Step 3 The difference between the maximum and minimum value is calculated using equation 6.

$$diff = cmax - cmin \quad (6)$$

Step 4 Then, the Hue value is calculated using equation 7.

$$H = \begin{cases} 60° * \left(\frac{G' - B'}{diff} * mod6\right) & cmax = R' \\ 60° * \left(\frac{B' - R'}{diff} + 2\right) & cmax = G' \\ 60° * \left(\frac{R' - G'}{diff} + 4\right) & cmax = B' \end{cases} \quad (7)$$

Step 5 The saturation value is calculated using equation 8.

$$S = \begin{cases} 0 \; if \; cmax = 0 \\ \frac{diff}{cmax} \; else \end{cases} \quad (8)$$

Step 6 The value channel value is calculated using equation 9.

$$V = 100 - cmax \quad (9)$$

using the above steps, the RGB channel of resized image is converted into HSV image. The sample output for the RGB to HSV conversion is shown in the figure 2.

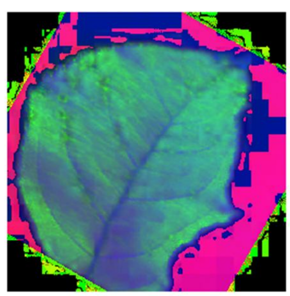

Figure 2. HSV image

An operation to extract features from the HSV-converted image was performed. The HSV value channel was separated out during the feature extraction process, and the histogram properties were computed.

C. *Extraction of histogram properties on Value channel*

In feature extraction process, the value channel of HSV was extracted and then its histogram properties were calculated. The sample output of value channel from HSV image is shown in the figure 3.

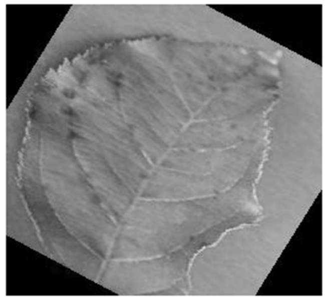

Figure 3. Value channel of HSV

Using histogram properties, three types of feature extraction are achieved. The following are the three types:
- Properties of first-order histograms
- Properties of second-order histograms
- Ternary pattern in the locality

In all these three methods, the histogram is utilized and the histogram calculation and its usage are different in each method.

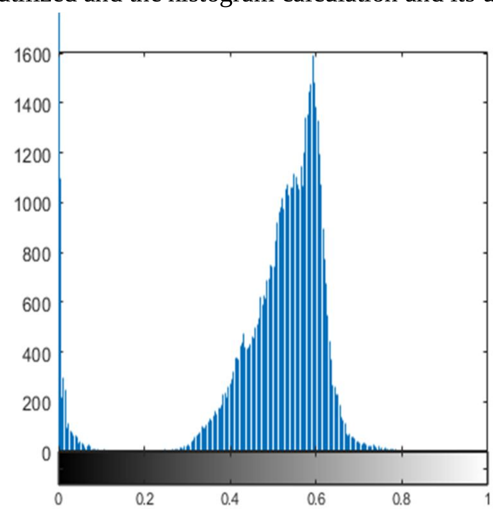

Figure 4. Pixel distribution count

The histogram is the graph between the number of pixel values (y-axis) and its counts (x-axis). Figures 3 and 4 illustrate an example histogram plot for the value channel of an HSV picture.

D. Properties of first-order histograms

The first order histogram properties were calculated based on the V channel values probability. The V channel probability level is based on its histogram count (V_{HC}) calculated using equation 10.

$$PL_v = \frac{V_{HC}}{I_R * I_C} \quad (10)$$

The above histogram count value is converted into single dimension using equation 11.

$$V_s = V_{HC}(:) \quad (11)$$

From the above equations, the following properties were calculated.

$$Mean = \sum PL_v .* V_s \quad (12)$$

$$Variance = \sum PL_v .* (V_s - \text{Mean}).^2 \quad (13)$$

$$T = PL_v .* (V_s - M).\hat{}3 \quad (14)$$

$$Skewness = V^{-3/2} * \sum T$$

$$T1 = PL_v .* (V_s - M).\hat{}4 \quad (15)$$

$$Kurtosis = T1^{-2} * \sum T$$

$$Entropy = \sum PL_v .* \text{IP} \quad (16)$$

$$Energy = \sum PL_v .* \log \text{IP} \quad (17)$$

Using equation 12 to 17, the properties of first order histograms were obtained.

E. Properties of second-order histograms

In this, the relation between the similar values was calculated using the co-occurrence matrix and pixel pair values. The pixel pair values were determined using equation 18.

$$P_p(m,n) = \sum_{i=1}^{x} \sum_{j=1}^{y} \begin{Bmatrix} 1, if \\ I(i,j) = m, \\ I(i + \Delta i, jj + \Delta j) = n \\ 0, otherwise \end{Bmatrix} \quad (18)$$

Using equations 19 to 20, the pixel pair count is utilized to derive the second order characteristics.

The following attributes were calculated: correlation (CR), contrast (c), energy(E), homogeneity (H), using co-occurrence matrix. The formula for computing these attributes is given in equations 10 through 13.

$$C = \sum_i |m - n|^2 P_p(m,n) \quad (19)$$

$$H = \frac{P_p(m,n)}{1 + |m - n|} \quad (20)$$

$$E = \sum_i \sum_j \{P_p(m,n)\}^2 \quad (21)$$

$$CR = \frac{\sum_{m,n} (m - \mu_m)(n - \mu_n) P_p(m,n)}{\sigma_m \sigma_n} \quad (22)$$

From these equations, the texture properties of the images were calculated.

F. Ternary pattern in the locality

Ternary pattern is also used to extract the texture features from the images. it is also depending on the histogram value. The steps that are used to derive the texture feature vector using ternary pattern is as follows.

Step 1 As this approach create a deep texture feature vector. It processes the image in blocks with size of 3 in width and 3 in height. A sample block values of an image is shown in the below figure.

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0.00784	0.00784	0.00784
0.03137	0.05490	0.01568
0.01960	0.08627	0.01568

Figure 4. Sample block values

Step 2 To normalize the values, compute the difference between the central pixel value with its neighbouring pixels. First stage of normalization output is shown in the below figure 5.

-0.0471	-0.0471	-0.0471
-0.0235		-0.0392
-0.0353	0.0314	-0.0392

Figure 5. 1st stage Normalization output

Step 3 The normalized output is obtained by encoding negative values to 0 and positive values to 1 as in figure 6.

0	**0**	**0**
0		**0**
0	**1**	**0**

Figure 6. Coding pixel values

Step 4 Figure 7 shows the final texture feature vector for a block. It is obtained by multiplying the step 3 output with its histogram count value.

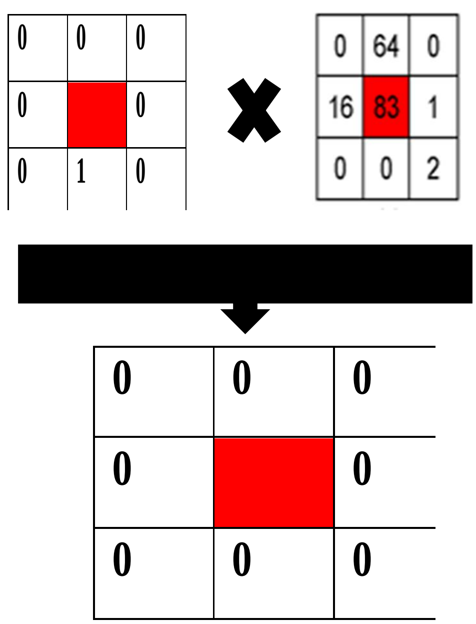

Figure 7. Sample texture vector output

Based on blocks, the ternary pattern output vector varies. In this, the length of vector output is ten.

The output from all the histogram properties is combined and it send to the feature reduction part to select the optimal two features using hybrid PSO-CSO approach.

Hybrid PSO-CSO based feature reduction

Here, the Hybrid Particle swarm (PS) and cuckoo search (CS) optimization was used to find the optimal features to identify the diseased leaf in the set. To perform this, it utilized the following objective function for both the optimization process.

$$of_{cso-pso} = \min(\mathrm{RNN}_{\mathrm{error}}) \quad (23)$$

The equation 23 is same for both the optimization process. In the first stage, the PS were employed to select the five features from the 11 feature set. The parameters and procedures for selecting features using PS algorithm is given below.

Table 2. PSO initialization

Parameter	Value
Search agents (particle)	50
Iteration	50
Weight	0.8
Learning weight (c1 and c2)	1.5 & 2.0
Lower bound	1
Upper bound	11
Number of outputs	5

Using Table 2 values, the initialization of PS begins and evaluates the swarms using equation 24 for the first iteration. For second iteration, the swarm update its velocity to update its position using equation 25 and 26.

$$v_{new} = r.coeff(iter_{best} - S_{cp} + (overall_{best} - S_{cp} \quad (24)$$

Where,

r.coeff = between 0 and 1

$iter_{best}$ = current iteration best value.

$Overall_{best}$= overall iteration best value

S_{cp}= swarm's current position

Using equation 25, the swarm new position will be calculated for the further iterations as in equation 26.

$$S_{np} = S_{cp} + v_{new} \quad (25)$$

From this, the optimal five features were obtained and it is further reduced using CS algorithm using table 3 parameters.

Table3. CSO Initialization

Parameter	Value
Search agents (Cuckoo)	20
Iteration (CSO)	20
Nest attraction	0.25
Lower bound	1
Upper bound	5
No of output	2

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The flow chart for the proposed HPSO-CSO approach for finding optimal attributes is shown in the below figure 8.

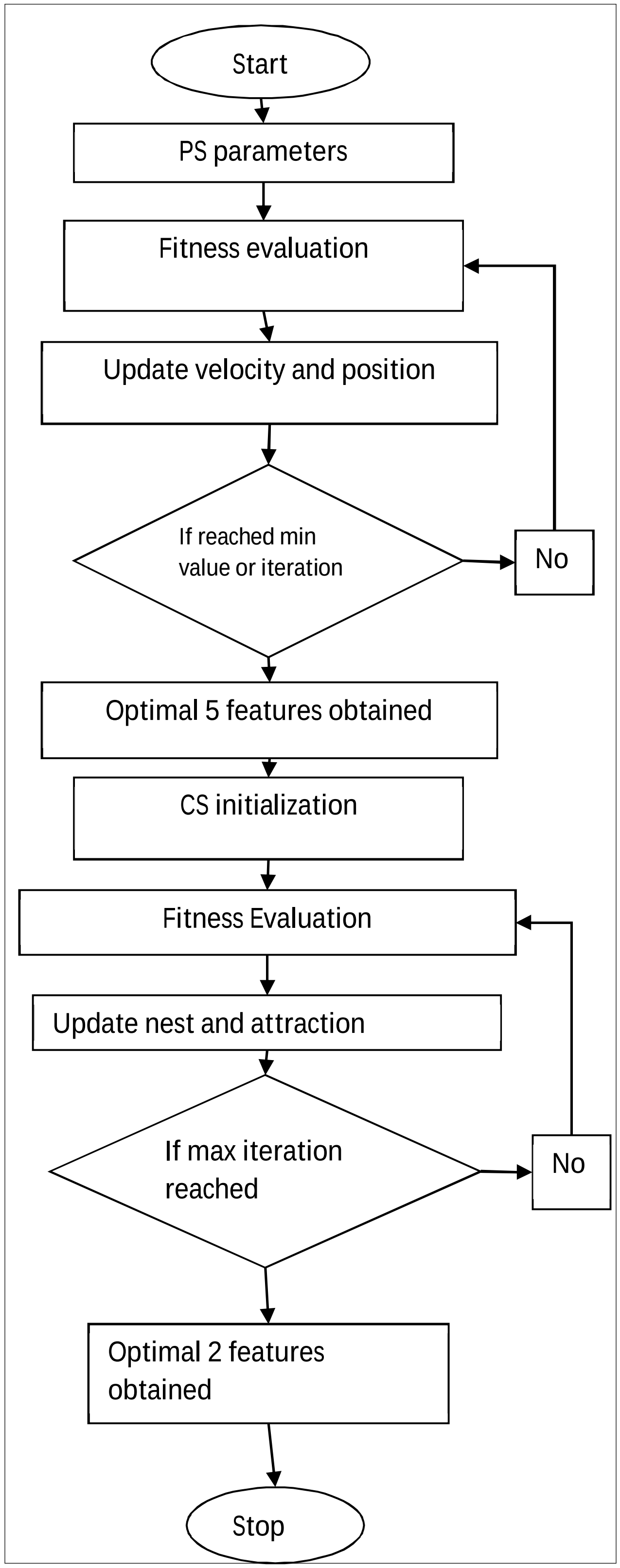

Figure 8. HPSO-CSO

Using the above flow chart steps and equations, the optimal feature set for classification was determined and given to the RNN.

V. REGRESSION NEURAL NETWORK

The optimal feature from hybrid PSO-CSO is partitioned into training and testing phases using a hold-out strategy of 0.3 percent. Seventy percent of the feature set is used for training, while the remaining thirty percent is used for testing. Figure 9 depicts the steps in the RNN construction process.

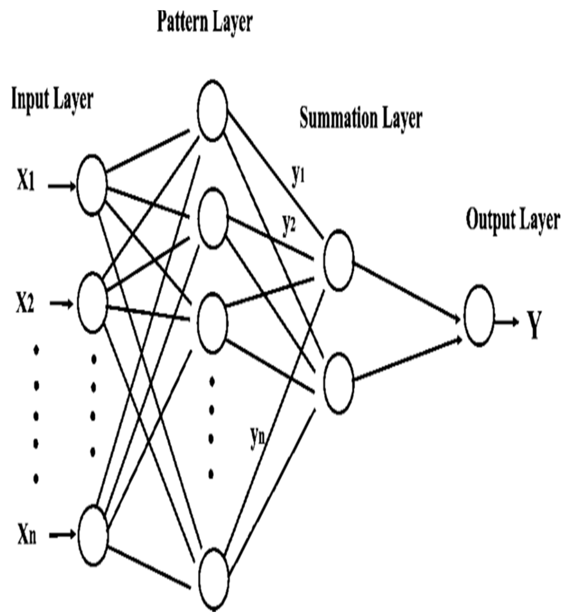

Figure 9. RNN flow diagram

Step 1 Inputs are act as the first layer of RNN. Here, the training feature set are used as inputs.

Step 2 The inputs are processed with kernel function using following equations to obtain input hidden neuron weights.

$$kernel(x, x_n) = e^{-k_d/2\sigma^2} \quad (26)$$

$$k_d = (x - x_n)'(x - x_n) \quad (27)$$

Step 3 In summation layer, the numerator and denominator parts were calculated.

- The step 2 output will act as the numerator.
- The kernel value will act as the denominator.

Step 4 In this, the final output is obtained by dividing the numerator and denominator as shown in the equation.

$$Y = \frac{\sum_{k=1}^{N} y_k * Kernel(x, x_n)}{\sum_{k=1}^{N} Kernel(x, x_n)} \quad (28)$$

Using the above process, the input dataset is trained and tested with the generalized regression neural network. Finally, the tested network performance is evaluated using accuracy, sensitivity and specificity.

Implementation and Result discussion

The proposed HPSO-CSO-RNN based leaf disease classification was realized in simulated form using MATLAB R2021b version in windows 10 environment.

On the dataset in [36], the proposed Image transform and hybrid optimization-based regression neural network for identification of diseases in leaves is evaluated. The table 4 shows the sample images for healthy and ill leaves.

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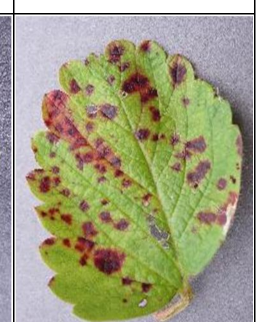
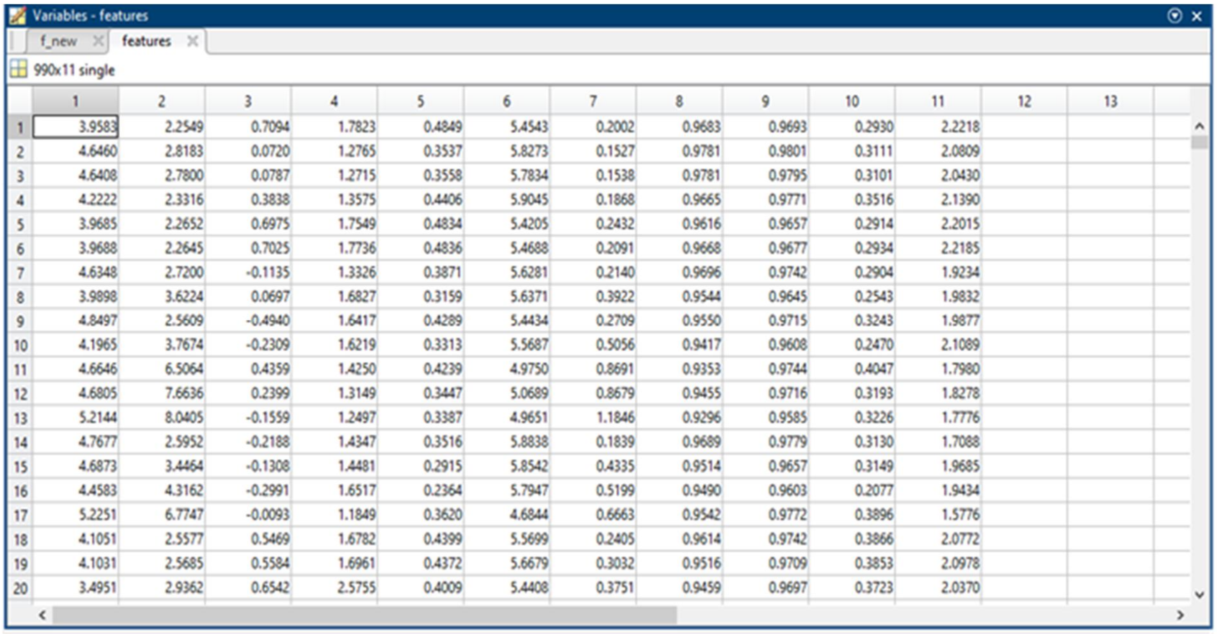
Table 4. Sample leaves for each leaf class

Image name	Without diseases	With diseases	Image name	Without diseases	With diseases
Apple			Peach		
Cherry			Pepper bell		
Corn			Potato		
Grapes			Strawberry		

The input images are transformed to an HSV image, and then the value channel histogram value for HSV images is computed, as shown in figures 3 and 4.
The feature extraction process is implemented on the pre-processed images through using histogram characteristics, as described in the extraction of features section. Figure 10 depicts the extracting features part's matching findings.


Variables - features
f_new | features
990x11 single

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	3.9583	2.2549	0.7094	1.7823	0.4849	5.4543	0.2002	0.9683	0.9693	0.2930	2.2218		
2	4.6460	2.8183	0.0720	1.2765	0.3537	5.8273	0.1527	0.9781	0.9801	0.3111	2.0809		
3	4.6408	2.7800	0.0787	1.2715	0.3558	5.7834	0.1538	0.9781	0.9795	0.3101	2.0430		
4	4.2222	2.3316	0.3838	1.3575	0.4406	5.9045	0.1868	0.9665	0.9771	0.3516	2.1390		
5	3.9685	2.2652	0.6975	1.7549	0.4834	5.4205	0.2432	0.9616	0.9657	0.2914	2.2015		
6	3.9688	2.2645	0.7025	1.7736	0.4836	5.4688	0.2091	0.9668	0.9677	0.2934	2.2185		
7	4.6348	2.7200	-0.1135	1.3326	0.3871	5.6281	0.2140	0.9696	0.9742	0.2904	1.9234		
8	3.9898	3.6224	0.0697	1.6827	0.3159	5.6371	0.3922	0.9544	0.9645	0.2543	1.9832		
9	4.8497	2.5609	-0.4940	1.6417	0.4289	5.4434	0.2709	0.9550	0.9715	0.3243	1.9877		
10	4.1965	3.7674	-0.2309	1.6219	0.3313	5.5687	0.5056	0.9417	0.9608	0.2470	2.1089		
11	4.6646	6.5064	0.4359	1.4250	0.4239	4.9750	0.8691	0.9353	0.9744	0.4047	1.7980		
12	4.6805	7.6636	0.2399	1.3149	0.3447	5.0689	0.8679	0.9455	0.9716	0.3193	1.8278		
13	5.2144	8.0405	-0.1559	1.2497	0.3387	4.9651	1.1846	0.9296	0.9585	0.3226	1.7776		
14	4.7677	2.5952	-0.2188	1.4347	0.3516	5.8838	0.1839	0.9689	0.9779	0.3130	1.7088		
15	4.6873	3.4464	-0.1308	1.4481	0.2915	5.8542	0.4335	0.9514	0.9657	0.3149	1.9685		
16	4.4583	4.3162	-0.2991	1.6517	0.2364	5.7947	0.5199	0.9490	0.9603	0.2077	1.9434		
17	5.2251	6.7747	-0.0093	1.1849	0.3620	4.6844	0.6663	0.9542	0.9772	0.3896	1.5776		
18	4.1051	2.5577	0.5469	1.6782	0.4399	5.5699	0.2405	0.9614	0.9742	0.3866	2.0772		
19	4.1031	2.5685	0.5584	1.6961	0.4372	5.6679	0.3032	0.9516	0.9709	0.3853	2.0978		
20	3.4951	2.9362	0.6542	2.5755	0.4009	5.4408	0.3751	0.9459	0.9697	0.3723	2.0370		

Figure 10. Feature extraction output

Figure 10 shows the features of each image class, with each row having 11 feature vectors for an image utilizing Value channel histogram characteristics. This 990*11 feature vector is used in particle swarm optimization to get the five best feature vectors for the second level of the feature reduction process.

Figure 11 depicts the relevant convergence curve for optimal feature selection after the PSO minimizes the objective function for 50 iterations employing 50 swarms.

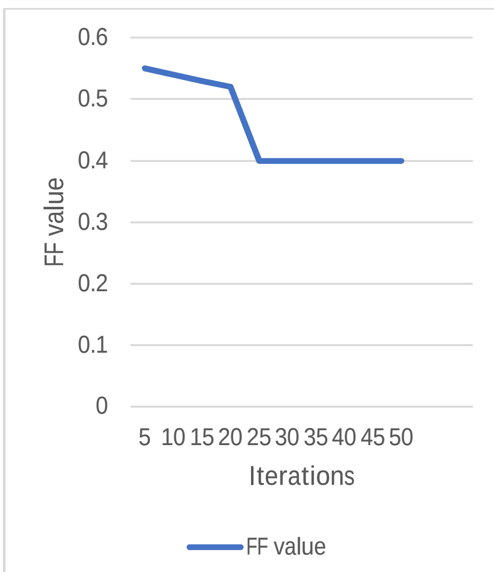


Figure 11. PSO convergence curve

Figure 11 demonstrates that the best feature is discovered after 25 rounds since the fitness function value has converged to 0.4 after 25 iterations. After 50 iterations, the five best characteristics are identified.

The Cuckko search method was used to compress the acquired optimum features to two features, and the related convergence curve is displayed in Figure 12.

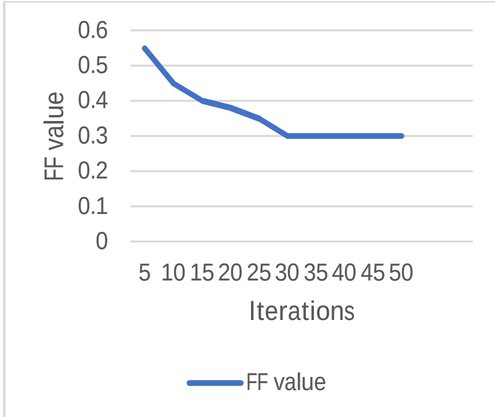


Figure 12. CSO convergence curve

Figure 12 demonstrates that the best feature is chosen after 25 rounds since the fitness function value has converged to 0.3 after 25 iterations. After 50 iterations, the two best characteristics are found.

Using the hold-out approach, the ideal feature set is divided into training and testing. 70% of the data was utilized to train the Regression neural network, with the remainder used for testing.

The studied network is then assessed in terms of accuracy, sensitivity, and specificity, and the proposed performance metrics are compared to the current PSO-based machine learning algorithm [37] and moth-based RNN.

Table 5. Performance analysis of leaf disease classification

Method/ Metric	Accuracy (%)	Sensitivity (%)	Specificity (%)
PSO-ML [38]	85.5	75.8	94
MFO-RNN	90	85.4	96.2
HPSO-CSO-RNN	93.6	96.2	97.8

According to the comparison table above, the proposed method outperformed the current methods by effectively recognizing all 33 classes. Image transformation and a hybrid feature selection approach are used to accomplish this.

As a result, the presented image transform and HPSO-CSO-based regression neural network are the most effective for classifying leaf diseases.

VI. CONCLUSION AND ITS ENHANCEMENT

This study proposed a machine learning strategy for classifying various leaf diseases using a minimal statistical model. The ideal feature set is automatically obtained by solving an objective function called minimize classifier error rate using image transform and hybrid PSO-CSO optimization. This capability cut GRNN's training and testing times in half. The proposed approach was tested on a Kaggle dataset and found to be the best machine learning algorithm for identifying leaf diseases.

In Future, the proposed method can be enhanced by processing the colour images directly for identifying the diseased region.

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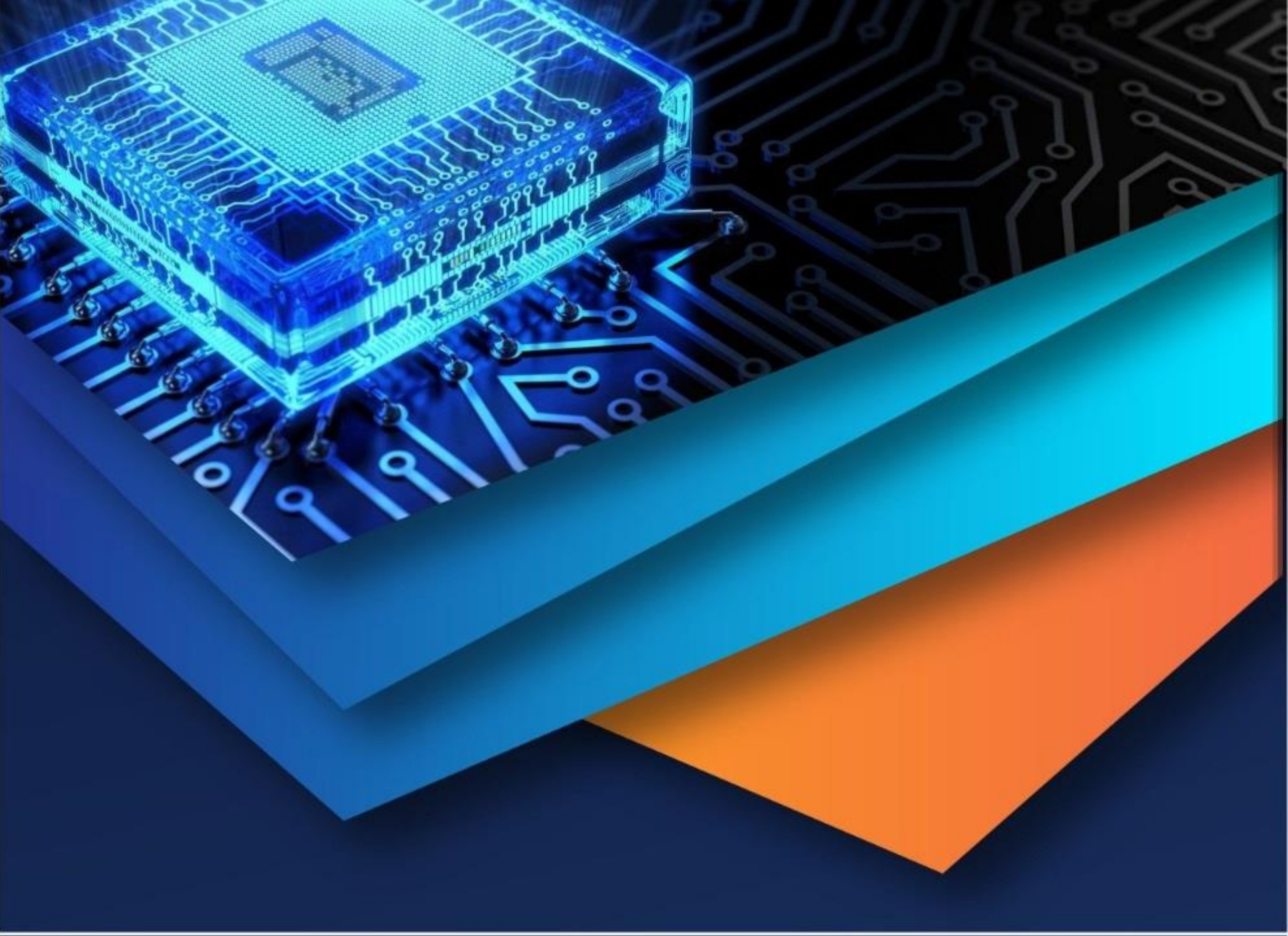

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