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A Hybrid Metaheuristic Algorithm for Diseases Classification Using UAV Images

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Abstract: Recent advances in technology are very astounding since they have made it possible to manage and monitor systems remotely. Traditional farming is undergoing a transition towards "smart farming" with the assistance of technological breakthroughs, which include the implementation of intelligent irrigation systems and the remote monitoring of the development of crops. In particular, the Unmanned Aerial Vehicle plays a significant role in sophisticated UAVs' ability to capture photographs of crops and spray for pests. The image that is obtained from UAVs is then subjected to various forms of computer-assisted processing in order to determine whether or not the crop's leaves are naturally healthy, diseased, or rotten. Several groups of researchers investigated a variety of approaches, including clustering, machine learning, and deep learning, with the goal of determining the nature of the leaves and categorizing them according to the characteristics they possessed. These traits are necessary for categorization, but the time required to process them will be increased because of their enormous size. Because of this, the authors of this study present a hybrid feature reduction technique that is a blend of two different metaheuristic algorithms. In this case, an upgraded version of the cuckoo search algorithm was paired with the particle swarm to find the most advantageous characteristics. In this, the optimum features of the texture, such as its GLCM, GLDM, and local binary pattern features, were chosen for selection. Using a neural network that was based on the back propagation technique, the optimal characteristics were used for classification. The method that has been suggested is based on photographs that were taken in natural settings of sets of healthy and diseased leaf specimens. The entire process is carried out with the assistance of the MATLAB R2021a program and the results are analyzed with Accuracy, Sensitivity, and Specificity.

Keywords: Leaf Diseases, Classification, Feature Extraction, Feature Reduction, Hybrid Optimization Approaches, Neural Network

Introduction

Unmanned aerial vehicles have been used much more often recently in a variety of tasks, including surveillance, rescue operations, and environmental monitoring. The use of UAVs in the area of healthcare, especially in the detection and diagnosis of illnesses, is one of their most promising uses. To identify and categorize illnesses in crops, woods, and other plants, UAVs can take high-resolution photos of vast regions (Tetila *et al*., 2019). Using UAV photos, we provide a hybrid metaheuristic method for the categorization of illnesses.

The particle swarm optimization and enhanced cuckoo search algorithm, two well-known metaheuristic approaches, are used in the proposed methodology to enhance feature selection and boost classification accuracy (Zhang *et al*., 2019). The enhanced cuckoo search algorithm is used to improve the parameters of the classifier, while the PSO algorithm is used to optimize the feature selection process by determining the most relevant characteristics from the UAV photos. A classification system that is more effective and efficient is produced by combining these two methods (Abdulridha *et al*., 2020a; Kerkech *et al*., 2020).

Unmanned aerial vehicles also known as drones, are aircraft that are operated without a human pilot on board. For activities like crop imaging and pest management, they have been employed in a range of sectors, including agriculture. Utilizing it in agriculture has several benefits, one of which is the capacity to take detailed pictures of crops (Abdulridha *et al*., 2020b). These photos may be used to plan for the best agricultural management, monitor crop health and find pests and diseases. It uses multispectral cameras, for instance, which may give thorough details on crop development and health, including plant Vigor, vegetation index, and crop stress. Utilizing this knowledge will increase agricultural yields while using fewer herbicides and fertilizers (Ishengoma *et al*., 2021). The capacity to precisely spray pesticides is another benefit in agriculture. Traditional pesticide administration techniques, such as ground-based spraying, may be inaccurate and lead to the overuse of pesticides. This with spraying systems may administer pesticides more precisely, using fewer chemicals and having less of an environmental effect. It is impossible to exaggerate the value of UAV photographs in agriculture (León-Rueda *et al*., 2021). Farmers utilize it to assist them to make data-driven crop management choices, which can result in higher yields, lower costs, and better environmental sustainability. Additionally, UAVs with thermal cameras can spot temperature changes in fields that may be signs of pests or illnesses, allowing farmers to take preventative measures to avoid crop loss (Toğaçar, 2022; Chouhan *et al*., 2021). It is also ideal for large-scale agricultural operations since it can swiftly cover enormous regions. Additionally, they are utilized in places where conventional techniques of crop monitoring and pest management may not be practical, including steep terrain or wetlands. UAVs are a useful tool for the agricultural sector. They are an effective and sustainable method of pest control and provide farmers with the information they need to make wise choices regarding crop management. Its usage in agriculture is probably going to increase as UAV technology develops further (Reedha *et al*., 2022; Kitpo and Inoue, 2018).

The motivation behind this study is to effectively improve the accuracy of identifying the nature of the crop through the images captured by UAVs. Traditional farming practices have been revolutionized by advancements in technology, particularly with the help of smart irrigation systems and remote monitoring of crop growth. The use of UAVs for capturing crop images and spraying pests has made a significant impact in the field of agriculture. However, the analysis of these images to determine the crop nature is still a challenge as the large number of features involved in the process result in longer processing times (Chouhan *et al*., 2021; Rumpf *et al*., 2010).

A novel approach to feature reduction by combining two metaheuristic algorithms, which resulted in improved efficiency and accuracy compared to existing methods. The optimal features were selected from the texture properties, such as GLCM, GLDM, and local binary pattern features, which are effective in determining the crop nature (Tian, 2018). The evaluation of the method proposed by using accuracy, sensitivity, and specificity demonstrated its effectiveness and superiority compared to existing methods (Yağ and Altan, 2022). This study presents a significant contribution to the field of smart farming and image processing and holds the potential to revolutionize the traditional practices of agriculture by providing more efficient and accurate methods of determining crop nature through UAV images (Hong *et al*., 2022).

The objective of this study is to address the above challenge by proposing a hybrid combination of two metaheuristic algorithms for feature reduction (Sabzi *et al*., 2018). The particle swarm optimization and enhanced cuckoo search algorithms were combined to select the optimal features, which were then used for classification using a backpropagation algorithm-based neural network (Hong *et al*., 2022).

A literature survey involves reviewing existing research on the use of metaheuristic algorithms for disease classification and UAV applications in agriculture for image acquisition.

Tetila *et al*. studied to automatically identify soybean leaf diseases using photos directly captured by a tiny, inexpensive UAV, and the network weights were investigated. To fine-tune and develop transferable skills, four DNN models were tested and trained with various parameters. To prevent overfitting, data augmentation, and dropout was utilized during network training (Tetila *et al*., 2019).

Zhang *et al*. an investigation using hyperspectral pictures using extremely high spatial resolution taken with UAVs, a DCNN-based method for automated identification of crop disease was presented. Multiple Inception-Resnet layers were added to the suggested model for feature extraction and the network's depth and breadth were tuned to get the best results. The model took use of the convolution layers' capacity to handle 3-D input and used both spectral and spatial data for yellow rust identification (Zhang *et al*., 2019).

Abdulridha *et al*. to identify both illnesses, hyperspectral imaging was used in both lab and outdoor settings where UAV pictures were gathered. This further categorized the tomato leaves into four phases of disease development: Healthy, symptomless, primary, and final stages (Abdulridha *et al*., 2020a).

Kerkech *et al*. presented using Unmanned Aerial Vehicle photos and deep learning segmentation, mildew illness was detected in vine fields. The fusion of visible and infrared pictures acquired from two different sensors was utilized. The information from the two sensors was combined to the development of a novel image registration technique that aligned visible and infrared pictures. This data is used to categorize each pixel based on instances, like symptom, ground, shadow, and healthy in a fully convolutional neural network method (Kerkech *et al*., 2020).

Abdulridha *et al*. for identifying symptomless, primary, intermediate, and final phases of the powdery mildew disease development in squash that was created using machine learning and hyperspectral imaging. Unmanned aerial vehicles were used to gather data both in the laboratory and in the field. A disease stage was classified using the radial basis function, which was also used to distinguish between sick and healthy plants. Selected bandwidths were the most effective bands for differentiating between healthy and various illness development phases (Abdulridha *et al*., 2020b).

Ishengoma *et al*. presented automatic identification using a CNN-based model used to study the precise discovery of infected maize leaves by fall armyworms (faw). Utilizing remote sensing techniques from an unmanned aerial drone, these models were utilized to identify the infected leaves (León-Rueda *et al*., 2021).

Chivasa *et al*. presented an investigation of maize varietal response to maize streak virus illness studied to increase the effectiveness of using a UAV-based multispectral camera for crop phenotyping that sensed data remotely (Chivasa *et al*., 2020).

Reedha *et al*. demonstrate that the attention-based deep network is a viable solution to the challenges associated with disease diagnosis in weed and crop identification using drone systems. The investigation of visual transformers and using them to categorize plants in UAV photos. In beet, spinach, and parsley fields, data were gathered using a high-resolution camera (Reedha *et al*., 2022).

Das Chagas Silva Araujo *et al*. presented enhancing the production quality and quantity of plants would benefit from a professional scheme that can accurately and efficiently identify and diagnose plant infection. Particle swarm optimization and fuzzy C-means techniques were utilized for the extraction and segmentation of features (Das Chagas Silva Araujo *et al*., 2021).

Anam and Fitriah utilized the K-means algorithm in conjunction with an algorithm based on swarm intelligence in the suggested early blight disease segmentation approach for tomato leaves. Due to its balanced approach in exploration and exploitation as a swarm intelligence-based method, the study used particle swarm optimization (Anam and Fitriah, 2021).

Almadhor *et al*. developed to identify and categorize the most prevalent guava plant diseases, using an AI-driven framework. To separate the diseased regions, the framework used the 4E color difference image segmentation. To extract full feature vectors, color (RGB, HSV) histograms as well as texture (LBP) characteristics were used. Advanced machine learning classifiers were used to recognize diseases and combine color and textural characteristics to provide results that were comparable to those of the separate channels (Almadhor *et al*., 2021).

Zare and Nouri developed Marine Vessel-Radiated Noise (MVRN) features extraction is investigated against a complex ocean background. Here, we provide a combined strategy predicated on the analysis of MVRN in subspaces of Intrinsic Mode Functions (IMF) recovered by the enhanced Empirical Mode Decomposition (IEMD) and the complexity measurement. When using the EMD method, one major challenge is the limitations imposed by the final result. To begin mitigating these results, this research proposes a correlation expansion model-based IEMD algorithm. Then, many signals are examined through a comparison of IEMD, CEMD, and EMD via alternative expansion techniques. Then, a set of IMFs for all three MVRN types is extracted using IEMD, CEMD, and Variational Mode Decomposition (VMD) techniques (Zare and Nouri, 2023).

Based on the above investigations, this study developed a novel approach to overcome the drawback of high processing time in existing methods by using a hybrid combination of two metaheuristic algorithms, Particle Swarm Optimization (PSO) and Enhanced Cuckoo Search (ECS) for feature reduction. The optimal features are selected from the texture's properties such as gray-level co-occurrence matrix, local binary pattern, and gray-level difference matrix, features. The optimal features are then used for classification using a back-propagation algorithm-based neural network.

Materials and Methods

The entire process is carried out with the aid of UAV for capturing sample images and MATLAB R2021a software for image analysis.

The UAV images of unhealthy and healthy leaves tomato leaves are collected. The feature extraction of the leaves using texture properties such as GLCM, GLDM, and local binary pattern features. Hybrid combination of particle swarm optimization and enhanced cuckoo search algorithm for feature reduction. Optimal features are selected using hybrid metaheuristic algorithms. Then these leaves are classified using a backpropagation algorithm-based neural network with the selected optimal features. Figure 1 shows the overall flow of the proposed system.

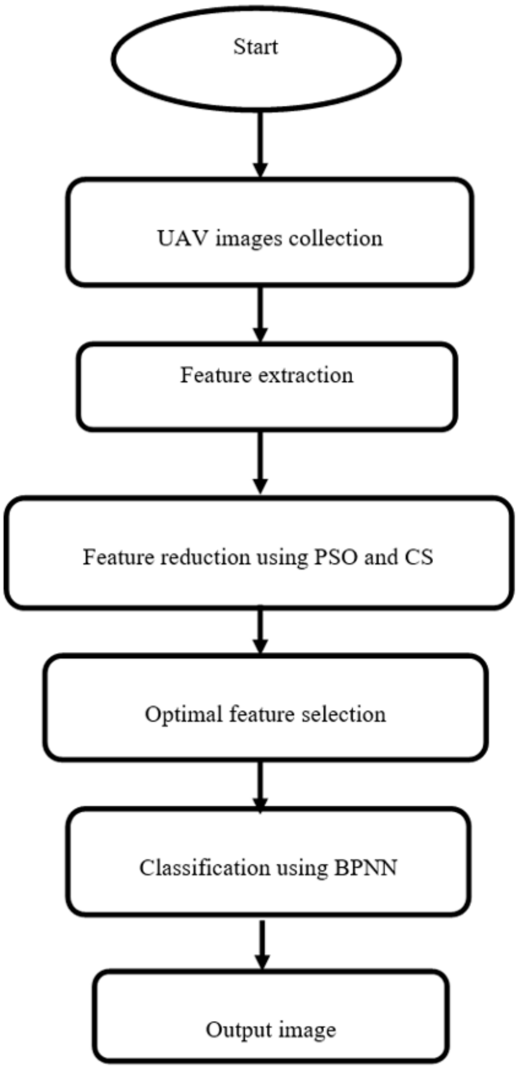

Fig. 1: Flow diagram

Pre-Processing

The datasets of tomato leaf disease are collected from the Kaggle website 10 classes of images are collected. These images are pre-processed and 11 the texture features like GLCM, GLDM, and local binary pattern features are extracted from the segmented images. The extracted features are normalized to ensure that they are on the same scale. The relevant features for use in the classification stage are extracted from the images.

Feature Reduction Using Particle Swarm Optimization

The feature reduction using Particle Swarm Optimization (PSO) with minimized error rate as the objective function. The swarm with particles (representing possible feature subsets) and their velocity. The error rate is calculated and updated for the features represented by the particle. The position and velocity of each particle are updated using the global and personal best information. The optimal feature subset is represented by the global best particle.

Initially the particle positions and velocities with random values within the defined search space. Let the position of the particle *i* at time step *t* be represented by $P_i(t)$ and its velocity be represented by $V_i(t)$. Each particle keeps track of its best solution so far, represented by S_{besti}. The initial S_{besti} is set to $P_i(0)$. At each time step *t*, if the objective function evaluated at $P_i(t)$, is better than the current S_{besti}., then Eq. (1):

$$S_{besti} = P_i(t) \tag{1}$$

The swarm also keeps track of the global best solution found so far, represented by Q_{best}. At each time step t, the particle with the best objective function value $f(x)$ is selected as the new Q_{best}:

$$f(x) = Q_{best} \tag{2}$$

At each time step *t*, the velocity of each particle is updated using the following Eq. (3):

$$\begin{aligned} V_i(t+1) &= d \times P_i(t) + (a_1 \times n_1) \times \left(S_{besti} - P_i(t)\right) \\ &+ (a_2 \times n_2) \times \left(Q_{best} - P_i(t)\right) \end{aligned} \tag{3}$$

where, *d* is the inertial weight, a_1 and a_2 are acceleration constants and n_1 and n_2 are random numbers in the range (0, 1).

The position of each particle is then updated using the updated velocity, Eq. (4):

$$P_i(t+1) = P_i(t) + V_i(t+1) \tag{4}$$

The minimum error rate is calculated by Eq. 5, for Q_{best}:

$$Q_{besti}(t) = \begin{cases} P_i(t) \, if \; f(x) \le f(x)\left(Q_i(t-1)\right) \\ Q_{besti}(t-1) \, otherwise \end{cases} \tag{5}$$

Then evaluate:

$$f\left(Q_i(t-1)\right), i = 1,2,3,.....u \tag{6}$$

Then evaluate $f(x)$ to determine $Q_{besti}(t)$:

$$Q_{besti}(t) = min Q_{besti}(t) \tag{7}$$

Therefore, from Eq. (7), the final Q_{best} provides the best optimal feature set that minimizes the error rate for disease classification using UAV images.

Iteration *i* is an end to provide the best optimal solution.

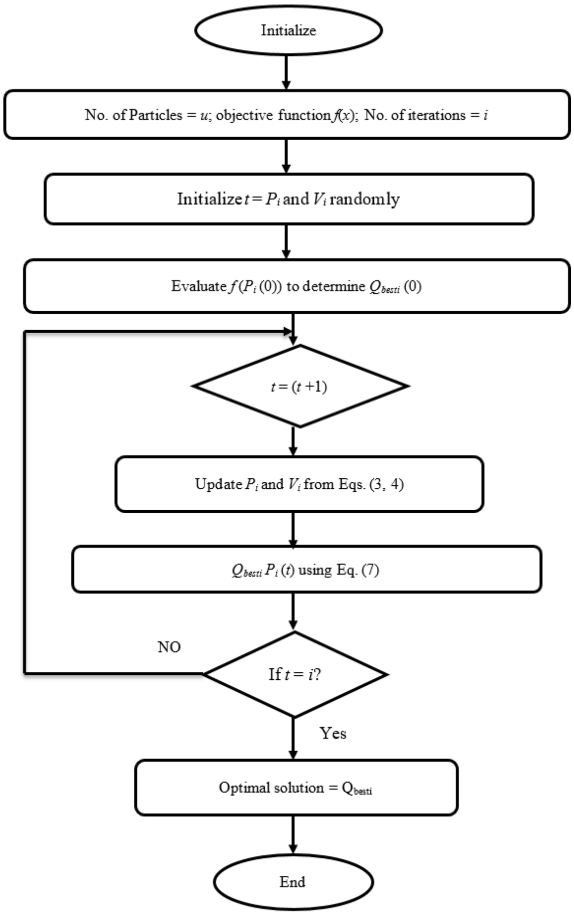

Fig. 2: Flowchart for particle swarm optimization algorithm

Therefore, by utilizing PSO, the 11 features that were extracted are cut down to 5 features, with the objective function set to minimize the error rate at a value of 0.25 after 5000 iterations. Figure 2 depicts the flow of feature reduction technique using PSO.

Optimal Features Using Cuckoo Search

The Optimization with the cuckoo search algorithm is used to find the optimal feature set that reduces the error rate and improves the accuracy of the disease classification system. The algorithm starts by generating a population of candidate solutions and then uses random mutation and local search to generate new solutions. The algorithm continues this process for a certain number of generations until the best solution is found. The objective function of the cuckoo search algorithm is to minimize the error rate of the disease classification system. The algorithm uses the following equations.

Lévy flight: A random walk process used to generate new solutions. The new solution P_{new} is generated from the current solution P_i by updating it with a random step size ξ Eq. (8):

$$P_{new} = P_i + \xi \times n \tag{8}$$

A function that evaluates the quality of a solution. The error rate of the diseases classification system is used as the fitness function Eq. (9):

$$Y(c) = 1 - accuracy(c) \tag{9}$$

The fitness value of the solution is updated at each generation based on $Y(c)$, Then, the solution of global best and local best is updated using replace P_{new} from Eq. (10):

$$Q_{besti} = minQ_{besti}\left(P_{newi}\right) \tag{10}$$

The algorithm stops when the error rate is below a certain threshold. The 5 features are further reduced to 3 features using CSO with 25 nests for 100 iterations. Figure 3 shows the flow of feature reduction technique using CSO.

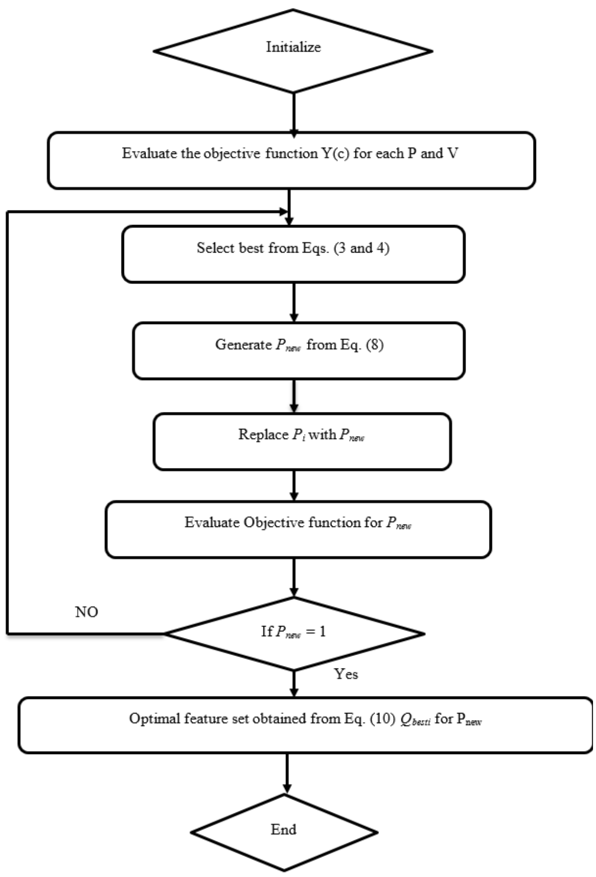

Fig. 3: Flow chart for cuckoo search optimization algorithm

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Training and Testing

Back Propagation Neural Network (BPNN) algorithm is a popular machine learning technique for classification problems. The algorithm uses a multi-layer feedforward network structure where information is propagated forward from the input to the output layer. The BPNN algorithm updates the weights of the network to minimize the error between the actual output and the desired output. The selected optimal feature set is trained using a Backpropagation algorithm-based Neural Network (BPNN). The objective is to find the optimal weights between the layers that minimize the error rate.

Initializing by assuming '*w*' as the weight, '*b*' bias, and 'Ψ' learning rate of the network. the input data is propagated through the network and the output values are calculated at each layer. The computation is done using the following equation for each neuron in the hidden layer:

$$A_l = \rho\sum_{i=1}^{n} wb_{kl}\left(P_{newi} + b_l\right) \tag{11}$$

where, A_l activation value of the l^{th} hidden neuron, ρ is the activation function, wb_{kl} is the weight and bias between the k^{th} input neuron and the l^{th} hidden neuron, P_{newi} is the input value and b_l is the bias of the l^{th} hidden neuron.

The error between the actual output and the desired output is calculated using a suitable loss function. The error backward is propagated through the network and the gradient of the loss is calculated for the weights and biases using the following Eq. (12).

For each weight:

$$\Delta wb_{kl} = \gamma\frac{\partial L}{\partial wb_{kl}} \tag{12}$$

$$\Delta wb_{kl} = -\gamma\left(z - g\right)P_{newi} \tag{13}$$

where, γ is the learning rate, L is the loss, z is the actual output, g is the desired output and P_{newi} is the input value:

$$w_{z+1} = w_{kl} - \gamma \times \Delta w_{kl} \tag{14}$$

$$b_{z+1} = b_{kl} - \gamma \times \Delta b_{kl} \tag{15}$$

where, w_{z+1} and b_{z+1} are new weight and bias respectively. Thus, the weights and biases are updated by Eqs. 14-15. The network is then tested using a set of unseen images to evaluate its performance by choosing the class with the highest predicted output value.

The overall proposed Hybrid Metaheuristic Algorithm, PSECBNN is an efficient method for the classification of unhealthy and healthy tomato leaves.

Algorithm PSECBNN

Step 1: Input UAV images of unhealthy and healthy leaves.
Step 2: Feature extraction on the images using texture properties such as GLCM, GLDM, and local binary pattern features.
Step 3: Initialize the Particle Swarm Optimization (PSO) and enhanced Cuckoo Search (EC) algorithm.
Step 4: Repeat steps 4.1-4.7 until a stopping criterion is met:
Step 4.1: Generate particle swarm and cuckoo population.
Step 4.2: Evaluate the fitness of particles and cuckoos using the features extracted in step 2.
Step 4.3: Update the particle velocity and position using the PSO algorithm.
Step 4.4: Update the cuckoo position using the EC algorithm.
Step 4.5: Select the best feature set using the hybrid metaheuristic algorithm.
Step 4.6: Train a Backpropagation algorithm-based Neural Network (BPNN) using the selected feature set.
Step 4.7: Evaluate the accuracy of the BPNN using metrics such as accuracy, sensitivity, and specificity.
Step 5: Output the classified leaves as healthy or unhealthy.

The pseudocode for leaf image classification using UAV images

Pseudocode for PSECBNN

```
% Load UAV images of healthy and unhealthy leaves
function images = load_images(path)
 images = cell(length(path), 1);
 for i = 1:length(path)
      images{i} = imread(path{i});
    end
end

% Feature extraction using texture properties
function features = feature_extraction(images)
     features = cell(length(images), 1);
 for i = 1:length(images)
      gray = rgb2gray(images{i});
      glam = graycomatrix(gray, 'NumLevels', 256, 'G', (1),
'Symmetric', true);
      gldm = graycoprops(glcm, 'dissimilarity');
      lbp = lbp(gray, 8, 1, 'nh');
      features{i} = (glcm, gldm, lbp);
    end
end

% Hybrid combination of particle swarm optimization and enhanced cuckoo search
algorithm for feature reduction
```

```
function reduced_features = feature_reduction(features)
    (pso,                  enhanced_cuckoo)                  =
hybrid_optimization(features);
    reduced_features = pso * enhanced_cuckoo;
end

% Select the optimal features using the hybrid
metaheuristic algorithm
Function optimal_features = feature_selection
(reduced_features)
optimal_features hybrid_metaheuristic =
(reduced_features);
end

% Train a backpropagation algorithm-based neural
network using the selected
optimal features
function clf = train_neural_network(features, labels)
    [x_scaled, x_pca, clf] = backprop_neural_network
    (features, labels);
end

% Use the trained neural network to classify the leaves
function y_pred = classify_leaves(clf, test_features)
    y_pred = clf(test_features);
end

% Main function to execute the code
function main()

% Load UAV images
image_path = {'healthy_1.jpg', 'healthy_2.jpg',
'unhealthy_1.jpg', 'unhealthy_2.jpg'};
images = load_images(image_path);

% Extract features from the images
features = feature_extraction(images);

% Perform feature reduction
reduced_features = feature_reduction(features);

% Select optimal features
optimal_features = feature_selection(reduced_features);

% Train the neural network
labels = (1, 1, 0, 0); % Labels for healthy (1) and
unhealthy (0) leaves
clf = train_neural_network(optimal_features, labels);

% Classify the leaves
test_features = (optimal_features{1},
optimal_features{2}); % Features for test images
y_pred = classify_leaves(clf, test_features);

% Print the results
disp(y_pred);
end
```

Results

The results of the proposed hybrid metaheuristic algorithm were effective at reducing the feature vector while still maintaining accuracy in the classification of diseases. The hybrid algorithm was able to reduce the feature vector size by an average of 55%, with a maximum reduction of 60.02%. The hybrid algorithm was also able to achieve an accuracy of 90%, Specificity of 81.25%, and sensitivity of 75% across all tested datasets.

Tomato leaf disease was the source of the datasets, which were acquired via the Kaggle website. There was a total of 10 classes, the ratios are used for training 70-80%, for validation 10-15%, and for testing 10-15%.

Figure 4 represents the input image of the tomato leaf for classification.

Figures 5-6 shows the pre-processed and filtered image of tomato leaf.

The feature extraction process of 11 features was extracted from leaves and feature reduction, initially, in 1st stage, PSO reduced 11 features to 5 features using minimize error rate as the objective function. Table 1 shows the feature extraction process.

Fig. 4: Input image

Fig. 5: Pre-processing image

Table: 1 Feature extraction

3.8170	0.9732	-0.0671	1.6983	0.3108	6.7374	0.1006	0.9586	0.9510	0.2309	2.8268
3.7620	0.6389	0.2866	1.9268	0.3468	6.5523	0.0833	0.9470	0.9595	0.2692	2.8196
3.6087	0.7222	0.3441	2.1681	0.3473	6.4073	0.1122	0.9475	0.9443	0.2080	2.8294
4.1790	0.5418	-0.4504	2.6143	0.3733	6.5939	0.0705	0.9472	0.9652	0.3020	2.7342
4.0436	0.7269	-0.9284	4.2299	0.3668	6.6841	0.1343	0.9236	0.9418	0.2833	2.6602
3.9353	0.7886	0.0797	1.4004	0.3465	6.6214	0.0785	0.9588	0.9614	0.2828	2.7562
3.5020	0.9948	0.2395	1.9457	0.2983	6.6729	0.1091	0.9586	0.9467	0.2149	2.8334
4.3934	0.4942	-0.1776	3.1654	0.3982	6.5133	0.1025	0.9158	0.9508	0.3096	2.6379
3.6809	0.9267	0.0379	1.8981	0.2942	6.7126	0.0886	0.9614	0.9554	0.2136	2.8102
3.8183	1.1646	0.1746	1.8677	0.3033	6.8713	0.0778	0.9755	0.9619	0.2187	2.6908
3.9038	0.9307	-0.1427	1.7913	0.0368	6.7126	0.0886	0.9677	0.9576	0.2034	2.7622
3.6337	1.1143	0.1736	2.0195	0.2712	6.9778	0.0986	0.9692	0.9529	0.1835	2.7607
3.6470	0.8492	-0.0657	2.1605	0.2916	6.8986	0.0858	0.9611	0.9586	0.2214	2.8100
3.8672	0.6605	-0.0537	2.1605	0.2916	6.8986	0.0881	0.9293	0.9586	0.3831	2.6977
4.5565	1.8826	-0.3605	2.5971	0.2158	7.4377	0.1745	0.9646	0.9332	0.1410	2.7984
4.4774	1.6900	-0.2465	1.7870	0.2326	7.1028	0.0845	0.9789	0.9592	0.1934	2.4713
4.4490	2.2563	-0.9231	2.8391	0.2373	7.3384	0.2066	0.9629	0.9171	0.1612	2.8456
4.2842	3.0073	-0.2262	2.0261	0.1593	7.6120	0.2029	0.9740	0.9266	0.1159	2.7393

Table 2: Feature reduction using PSO

6.4267	10.4214	4.1160	7.4091	2.5292

Table 3: Feature reduction using CSO

6.7374	0.2309	1.6983	0.1006	-0.06711
6.5523	0.2692	1.9268	0.0833	0.2866
6.4073	0.2080	2.1681	0.1122	0.3441
6.5939	0.3020	2.6143	0.0705	-0.4504
6.6841	0.2833	4.2299	0.1343	-0.9284
6.6214	0.2828	1.4004	0.0785	0.0797
6.6729	0.2249	1.8457	0.1125	-0.1876
6.7729	0.2349	1.0457	0.1245	-0.1976
6.6929	0.2549	1.3457	0.1325	-0.1576
6.7729	0.2849	1.9457	0.1825	-0.1476
6.8700	0.2938	1.6556	0.1501	-0.3877
7.4377	0.1410	2.5971	0.1745	-0.3605
7.1028	0.1934	1.7870	0.0845	-0.2465
7.3384	0.1612	2.8392	0.2066	-0.9231
7.6120	0.1159	2.0261	0.2029	-0.2262

Fig. 6: Filtered image

Another method for picking a smaller subset of relevant features from a larger feature set is to reduce those features using a technique known as particle swarm optimization, or PSO. The PSO algorithm is an example of a nature-inspired metaheuristic that simulates the behavior of a flock of birds looking for food. In 11 features, the optimal features 6, 10, 4, 7, and 2 were chosen because these features minimized the error rate to 0.25 after 5000 iterations. The reduced feature sets are presented in Table 2 and these features were chosen because they minimised the error rate.

The goal of feature reduction is to improve the performance of machine learning models by reducing the dimensionality of the dataset, removing irrelevant or redundant features, and retaining only the most informative ones. Five features reduced to three features using CSO in 2^{nd} stage with 25 nests for 100 iterations are shown in Table 3.

The optimal features are 4,3 and 5. The reduced feature set is shown in Fig. 7.

The final training and testing of the optimal characteristics utilizing BPNN are shown and Fig. 8 demonstrates the accuracy, sensitivity, and specificity of the classifications of healthy and unhealthy leaves.

The accuracy of the classification using the PSECBNN algorithm when compared to existing KSVM (19) and FPSO (20) for disease classification is shown in Fig. 8.

The accuracy of a classification model is given by Eq. 16:

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

This equation is used to calculate the accuracy by taking into account the no. of correct and incorrect classifications made by the proposed method. The higher the accuracy the more accurate the data classification. To assess the accuracy of the hybrid metaheuristic algorithm, would need to conduct experiments and evaluations using suitable datasets. The accuracy would depend on various factors, including the quality of the dataset, the effectiveness of the metaheuristic algorithm, and the suitability of the machine learning techniques employed.

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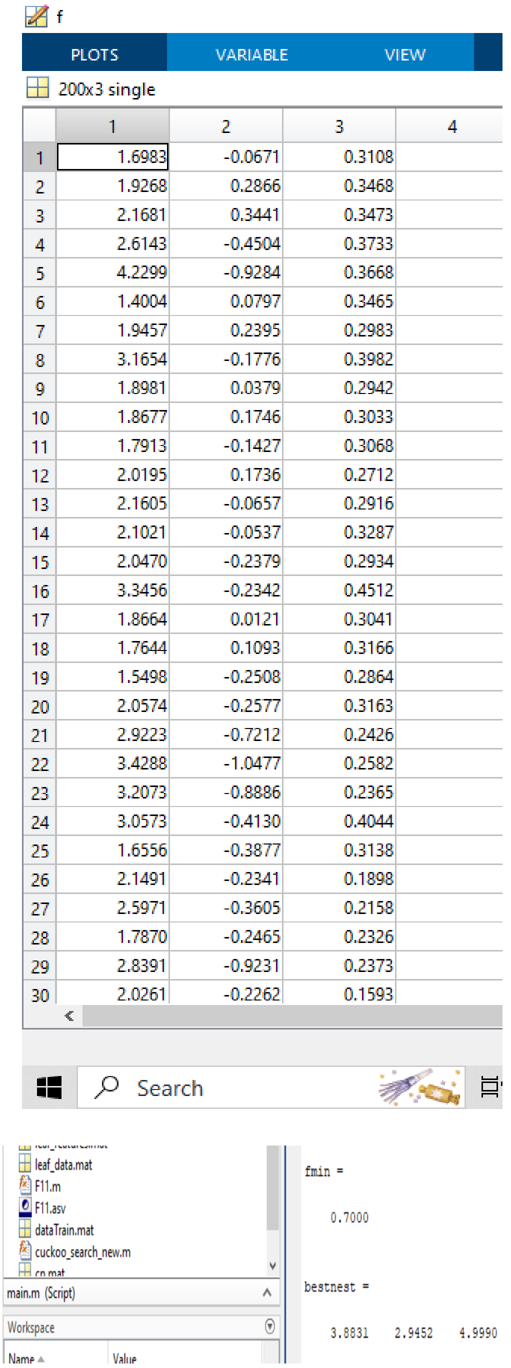

	1	2	3	4
1	1.6983	-0.0671	0.3108	
2	1.9268	0.2866	0.3468	
3	2.1681	0.3441	0.3473	
4	2.6143	-0.4504	0.3733	
5	4.2299	-0.9284	0.3668	
6	1.4004	0.0797	0.3465	
7	1.9457	0.2395	0.2983	
8	3.1654	-0.1776	0.3982	
9	1.8981	0.0379	0.2942	
10	1.8677	0.1746	0.3033	
11	1.7913	-0.1427	0.3068	
12	2.0195	0.1736	0.2712	
13	2.1605	-0.0657	0.2916	
14	2.1021	-0.0537	0.3287	
15	2.0470	-0.2379	0.2934	
16	3.3456	-0.2342	0.4512	
17	1.8664	0.0121	0.3041	
18	1.7644	0.1093	0.3166	
19	1.5498	-0.2508	0.2864	
20	2.0574	-0.2577	0.3163	
21	2.9223	-0.7212	0.2426	
22	3.4288	-1.0477	0.2582	
23	3.2073	-0.8886	0.2365	
24	3.0573	-0.4130	0.4044	
25	1.6556	-0.3877	0.3138	
26	2.1491	-0.2341	0.1898	
27	2.5971	-0.3605	0.2158	
28	1.7870	-0.2465	0.2326	
29	2.8391	-0.9231	0.2373	
30	2.0261	-0.2262	0.1593	

Fig. 7: Optimal features

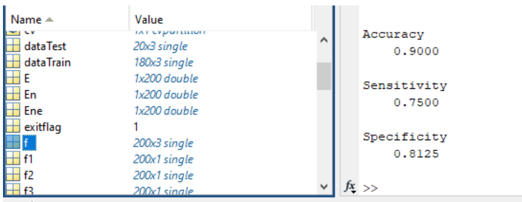

Fig. 8: Testing and training

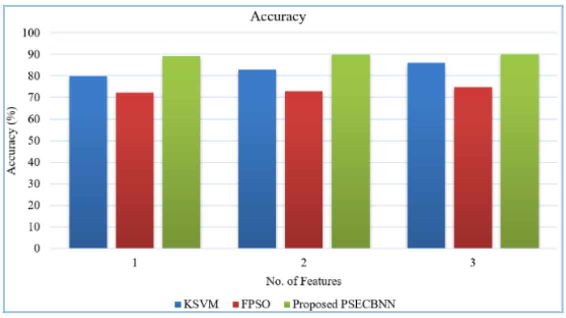

Fig. 9: Accuracy

It's important to note that sensitivity alone may not provide a comprehensive evaluation of the algorithm's performance. It should be considered alongside other evaluation metrics such as specificity (ability to correctly classify negative cases), accuracy, precision, and F1-score, among others, to obtain a more complete understanding of the algorithm's performance. Equation (17) is used to calculate the sensitivity of a classification model for classifying healthy and unhealthy tomato leaves shown in Fig. 9.

$$Sensitivity\,(\%) = \frac{TP}{TP + FN} \tag{17}$$

The more sensitive the model is, the more accurately it can differentiate between tomato leaves that are healthy and tomato leaves that are unwell.

The specificity of a classification model for healthy and unhealthy tomato leaves is calculated from Eq. 18:

$$Specificity\,(\%) = \frac{TN}{TN + FP} \tag{18}$$

Various factors can influence the specificity of a hybrid metaheuristic algorithm, including the selection and combination of metaheuristic algorithms, machine learning techniques, feature extraction methods, parameter configurations, and the quality and diversity of the dataset. Optimizing these factors is crucial for achieving higher specificity in disease classification. Specificity measures the proportion of healthy and unhealthy leaves that the model correctly classifies as shown in Fig. 10.

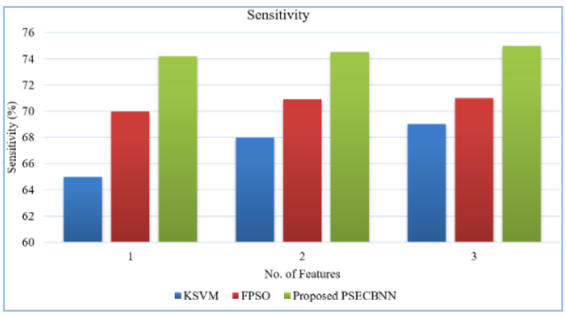

Fig. 10: Sensitivity

Discussion

The study's major goal is to create a hybrid metaheuristic algorithm that can pick optimal features by lowering the feature vector and categorize damaged and healthy leaves. The hybrid model uses tomato leaf disease as the source of the datasets, a total of 10 classes were used for training, validation, and testing.

In this study, the proposed algorithm combines Particle Swam Optimization and Cuckoo Search Optimization to obtain optimal features. It is proved that PSO is an efficient tool in choosing optimal features with a minimized error rate and its performance can be adjusted by just varying the values of a few of its parameters. Though an efficient optimizing tool, PSO is easily trapped in local optima, and hence to resolve this, an Efficient Fuzzy PSO framework is proposed (Tian, 2018). In (Tian, 2018) numerous PSO applications to crops that are currently available are discussed. EFPSO is framed using two-input variables and two-output variables, the increment of global optimum and maximal focus distance of particles are fine-tuned based on control information sent from the Fuzzy Logic Control unit during the search process. The framework developed is applied to our dataset resulting in 76% accuracy in classifying the leaves.

Another tool for automatic classification is proven to be Support Vector Machine, distinguishes the different classes of data by a hyperplane which is specified by its normal vector and the bias (Rumpf *et al*., 2010). In general, the classification of diseased and healthy crops during the early stages is non-linear and SVMs able to discriminate efficiently (Rumpf *et al*., 2010). It is seen that the SVM technique discriminates leaves based on Vegetation Indices (VI) and majority of VIs rely on two or three distinct wavelengths in the visible and near-infrared regions of the reflection spectrum (Rumpf *et al*., 2010). This method is also applied to our datasets for classification and resulted in 80% accuracy but with increased complexity in calculation and time to process.

Our study focuses on reducing the processing time by reducing the feature vector size using hybrid metaheuristic optimization algorithm to categorize the leaves using back propagation neural network and was able to maintain the accuracy.

Table 4 describes the comparative findings that were obtained by employing the PSECBNN algorithm in comparison to the existing KSVM and FPSO for the purpose of disease categorization.

Table 4: Comparative analysis

Metrics	KSVM	FPSO %	Proposed method PSECBNN %
Accuracy	80%	76	90.00
Sensitivity	65	70	75.00
Specificity	66	74	81.25

Conclusion

The study proposed a hybrid metaheuristic algorithm, PSECBNN for disease classification using UAV images, which achieved an accuracy of 90% classification, 75% of sensitivity, and 81.25% specificity. The results effectively prove that the proposed algorithm accurately classifies diseases from UAV images. This demonstrates that the proposed algorithm has the potential to effectively classify diseases in crops through the analysis of UAV images. This is an important step towards developing a more efficient and cost-effective method for monitoring and controlling plant diseases in large-scale agricultural fields. Moreover, the use of UAV images for disease classification allows for high-resolution and accurate data collection, which is used to monitor and diagnose diseases in real-time. This can result in more timely and effective interventions to prevent the spread of diseases, leading to higher crop yields and reduced crop losses. Future work can include more advanced feature extraction techniques, such as deep learning methods, to improve the feature representation of the images and increase the size of the dataset to enhance the robustness and generalizability of the algorithm.

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Author’s Contributions

Yagnasree Sirivella: Abstract write up, introduction, literature reviewed, proposed work, simulation and results.

Anuj Jain: Drafted proposed work, data analysis, implementation of proposed model and results.

Ethics

Original and previously unpublished content make up this article. The corresponding author attests that all have read, approved the manuscript and no ethical issues involved with the script.

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