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Whale Optimized Deep Model for Paddy and Maize Leaf Disease Detection

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Abstract- Plant disease management is an essential process to minimize loss in the field of agriculture. Plant leaf disease detection(PLDD) technology helps the formers to reduce the loss of quality yield production. This study focuses on detecting paddy and maize plant leaf disease-detecting methods. It contributes to a PLDD method to improve detection accuracy and overall performance. The PLDD method introduced a whales-optimized artificial neural network (WOANN) method for classifying the four Maize and four rice leaf disease-related classes. The WOANN uses the whale optimizer's food-searching functionalities to improve the performance and detection accuracy of the dense net model. This WOANN classifies the maize leaf light, maize grey leaf spot, maize common rust, rice bacterial leaf blight, rice bacterial leaf steak, rice brown spot, and healthy leaves of both Maize and paddy. It uses the Hilbert-Schmidt independent criterion lasso correlation algorithm to support the WOANN classifier in selecting the significant features. The performance analysis shows that the WOANN-based approach achieves a maximum of 99.35% detection accuracy for maize leaf disease and 99.13% for paddy leaf disease. Its efficiency analysis shows that the WOANN-based approaches achieve a maximum accuracy rate than comparison approaches.

Keywords- Artificial neural network, Maize leaf disease, Paddy leaf disease, Whale optimizer, Plant disease detection

1. Introduction

Plant disease controlling [1] is important to reduce crop losses. Crop loss may be as high as 75 per cent, and a million hectares of rice are infected yearly. The most economically important hosts are paddy and Maize. These two crops are commonly affected by some bacterial and fungal infections [2]. This study analyzes some common leaf diseases [3,4], including brown spots, bacterial leaf blight, leaf streaks, common corn rust, corn grey spot, corn leaf blight and more. These infections cause crop loss and economic loss for the farmers. Fungal and bacterial infections on crops occur at all stages of plant growth, from seeing to ear to the heading stage. The symptoms of these infections appear in various parts of the crop, including nodes, leaves, glumes, and rachis. Brown spot [5] is a fungal infection that infects a crop's leaves, spikelets, sheaths, and glumes. The most visible damage is the numerous big spots on the leaves, which can kill the whole leaf. This infection is found in high relative humidity areas and temperatures between 16 to 36 degree Celsius. It normally occurs in soil with nutrition deficiency and unflooded soil, which accumulates toxic substances. This infection origin both quality and quantity losses. Every year 5% of yield loss across all low-land rice production. Bacterial leaf blight(BLB) [6] of paddy is a deadly leaf disease. It is one of the most common leaf-damaging diseases of cultivated rice. It is devastating if it comes early—yield losses from 20% to 70% annually in India. BLB-affected paddy leaves appearances changed as grey-green or yellowish-white streaks with wavy edges starting from the tips to the base, then slowly drying up and dying. Once this infection affects the plant at boosting stage, it does not affect the yield but the rice quality.

Leaf streak [7] identification is essential in paddy crops. Infected plans need to be removed from the field to prevent spreading. It shows brown to greyish-white lesions, which turn dry when the disease is severe.

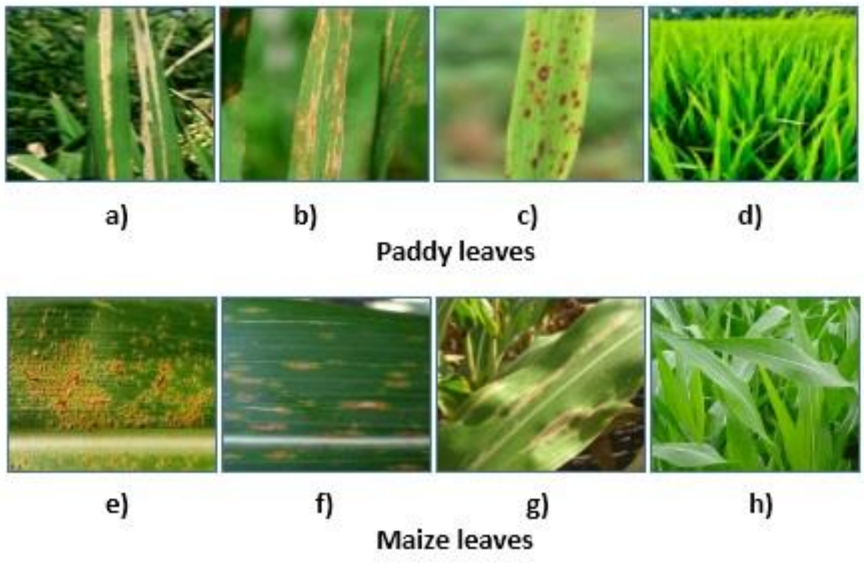


Figure 1: Sample infected and healthy leaves of paddy and Maize

Figure 1 a), b), c), and d) shows the sample infected and healthy paddy leaves, including Bacterial leaf blight, bacterial leaf streak, brown spot, and healthy paddy leaves, respectively. Figure 1 e), f), g), and h) shows the sample infected and healthy maize leaves, including common corn rust, corn grey spot, corn leaf blight, and healthy maize leaves, respectively.

Canoe-shaped lesions appear in corn leaf blight[8] infected leaves. The lesion size is between 1 and 6 inches long, but the size might vary for different hybrid resistance genes. A grey-green border surrounds it. Lesions start from lower leaves and spread over upper leaves as well. This corn leaf disease causes significant grain loss if susceptible hybrids are infected before silking. Common rust [9] is a foliar infection of corn affected by moist and cool environments. Lesions start as flecks on leaves that grow into tiny tan spots. These spots changed into lengthened brick red to cinnamon brown pustules with a jagged appearance. It creates significant damage to upper leaves early in the life of the hybrid, resulting in higher yield losses. Corn leaf spot[10] is the most serious infection in countries like the U.S. It appears in high humidity and warm conditions. The appearance confuses other foliar maize diseases. It commonly starts in small necrotic spots with halos in rectangle-shaped lesions about 2 to 3 inches. The colour starts from grey to brown in appearance.

The above-discussed six diseases majorly infect maize and paddy crops[11-14]. This infection creates major losses for the formers. The formers must identify the infections early to control the spread by taking appropriate disease control procedures. Accurate disease detection requires plant experts' knowledge, but it takes a long time to identify the infection types and get expert advice. So, formers friendly symptoms-based disease detection approach is essential to reduce the limitations. The researchers initiated many leave-based disease detection approaches [15-17]. However, still accurate leave disease detection is challenging for researchers. So, this study aims to detect paddy and maize leaf disease accurately. An optimized deep-learning model is developed to identify these diseases accurately. Moreover, this study also designed this leave disease detection model with some testing features to improve the detection performance.

Background Study

This section prepares the background study on plant leaves disease detection and its methodologies. S. Ramesh et al., 2020[18] designed an optimized deep model-based paddy leaves disease detection method. This model is designed to classify bacterial blight, leaf blasts, brown spots, leaf sheath rot, and normal paddy leaves. The optimized deep model uses the Jaya optimizer to enhance the performance of the deep model. This model obtained a maximum of 98.9% classification accuracy for paddy leaf blast disease.

Akrati Nigam et al., 2020[19] developed a Butterfly optimizer optimized deep-learning model for four different paddy leaf diseases images like bacterial leaf blight, sheath rot, healthy leaf, and brown spot. The Principal Component Analysis (PCA) is applied for the plant disease features, and the optimized deep model classifies the leaf disease. This model obtained a maximum of 98% accuracy and 0.0100% entropy loss for paddy leaf disease detection.

Madhu et al., 2021[20] introduced an edge detection-based optimized deep model for paddy leaf disease. It uses a canny edge detection method to identify the edges to train the optimized deep model. Moreover, the clustering method is applied to segment the infected portions from the original images to reduce the processing time and space utilized by the edge detection method. It helps improve the deep model's edge detection performance and classification accuracy.

Qjan X et al., 2022[21] developed a transformer and self-attention-based Convolutional neural network(CNN) model to detect three different Maize diseased and healthy conditions corn leaf blight, grey leaf spot, normal, and corn rust. It performs visual information of the local region of images by tokens, calculates the attention mechanism(correlation) of information between local regions, and integrates the global information to perform disease classification decisions.

Ma L et al., 2023[22] Introduce an improved version of the YoLOv5n model to detect maize leaf disease. This model incorporates the coordinate attention mechanism, swin transformer head, and CTR_YoLOv5n to build the detection phase. The average maize disease detection accuracy achieved by the WG-MARNet model is 95.4%.

Li Z et al., 2022[23] designed an intelligent maize plant leaf disease monitoring system. This system introduces a deep learning(DL) model, namely WG-MARNet, to detect three commonly occurring maize diseases and healthy leaves. It is an extended version of the ResNet50 model. This WG-MARNet model achieves a maximum of 97.43% classification accuracy.

R. Sujatha et al., 2021 [24] analyzed various machine learning(ML) and DL models' performance while detecting plant leaves disease. This analysis uses three ML models and three DL models. Random forest and support vector machine(SVM) with stochastic gradient descent techniques are used as the ML models, and VGG-16, VGG-19, and Inception V3 model is used as DL models to perform the analysis. The analysis results show that the SVM and VGG-16 models obtained a maximum of 87% and 87.4% as classification accuracy.

Trivedi J et al., 2020[25] utilized the CNN model to detect leaf disease. It uses 54305 leave image data and 38 classes for training and testing the CNN model performance. This performance analysis shows that the CNN classifier achieves 95.8% as the maximum accuracy rate.

N. Kanaka Durga et al., 2019 [26] inspect the plant leaves disease using ML models. This inspection focuses on underfitting data reduction—the histogram-oriented gradient(HOG) method for feature extraction. The ANN and SVM classifier is used to evaluate the classification performance. The results show that the ANN classifier obtained a maximum of 85% tomato disease detection accuracy.

B.B. Damodaran et al., 2017 [27] Designed a feature selection method for hyperspectral image classification. A new class separation measure called surrogate kernel and Hilbert Schmidt independence criteria (HSIC) is used to measure the feature importance of each feature. It aligns the empirical kernel map in the RKHS.

Yang P et al., 2023[28] introduced an optimized DL model for electronic current transformers(ECT) fault diagnosis. This diagnosis model uses the radial basis function neural network (RBFNN) for classification, and the whale optimization algorithm(WOA) is used for RBFNN's parameter optimization. The WOA easily fall for local optimum. A chaotic map strategy is introduced to enhance the population diversity. Nonlinear convergence factor and adaptive weight are used to improve the exploitation ability. Finally, to ensure the convergence speed, it uses the modified simulation analysis technique to prevent premature convergence. The performance analysis shows that the optimized DL model achieves a maximum of 97.77% classification accuracy.

K.K Nivethithaa et al., 2023 [29] Introduced a fish swarm optimized SVM model for paddy and Maize leaves detection. This FSO algorithm improves the performance of the SVM classifier by optimizing the parameters to improve the accuracy rate. The performance analysis demonstrates random behaviour of the FSO helps the SVM classifier to improve the disease detection accuracy rate by up to 98.9% for maize disease.

Finding the potential model for crop disease is the major challenge in agricultural research. The related studies state that Maize and paddy are the two major crops worldwide. The crop infection creates major losses for the farmers and food production. Most of the ML and DL models discussed in this study could perform better in leaf disease detection. Optimized classification models perform better in reducing the fitting issues and optimizing the model functionalities. Still, this model failed to achieve a reliable accuracy rate. So, this study combines the food hunting multi-objective behaviours of WOA with the ANN model to improve the model performance for paddy and maize disease detection.

Whale-Optimized Deep Model For Plant Leave Disease Detection

This section describes various methodologies for optimized deep model-based paddy and Maize leaves disease detection approaches. It describes the stages of the proposed leaf infection detection approach.

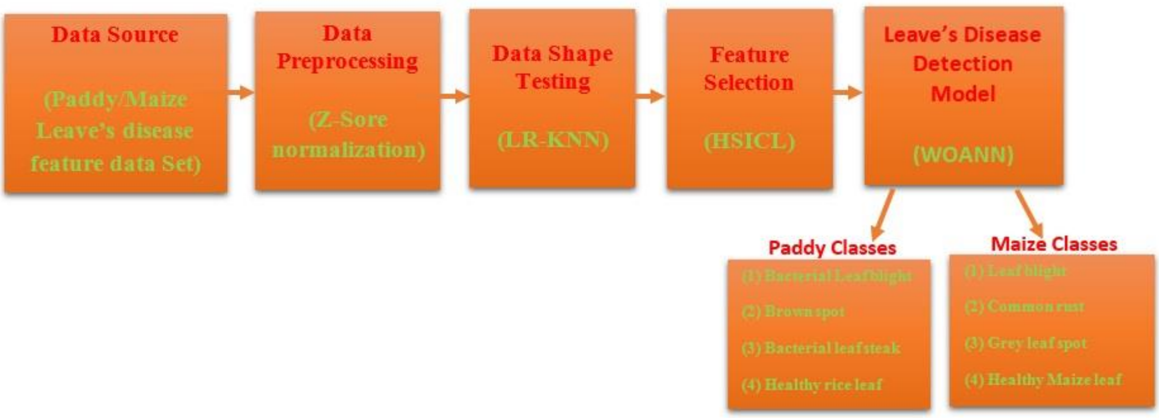


Figure 2: Flow of WOANN-based paddy and Maize leaves disease detection

Figure 2 illustrates the general workflow of the WOANN-based paddy and Maize leaves disease detection approach. It contains three main phases: data preprocessing, feature selection, and classification. The data preprocessing phase contains feature regularization and data shape testing phase. The plant follows the feature selection phase and leaves the disease classification phase.

A. Data Sources

This study uses two leaf disease feature datasets, including paddy and maize leaves to evaluate the performance of the WOANN model. These two datasets are taken from the Kaggle database [30,31]. The Paddy dataset contains 478 bacterial leaf blight disease records, 965 brown spot disease records, 380 leaf streak disease records, and 1764 healthy paddy records. Similarly, the Maize dataset contains 1145 corn blight disease records, 1306 corn common rust, 574 grey corn spots, and 1163 healthy maize leaves records. The model training phase uses 70% samples, and the testing phase uses 30% of the samples. The training or testing process of paddy and Maize leaves disease are performed separately.

Paddy leaf disease dataset										
Class	Area	Perimeter	Aspectratio	Rectangularity	Circularity	Equidiameter	Contrast	Correlation	Inverse Difference Moments	Entropy
1	1.66E+04	6.96E+02	2.17E+00	1.82E+00	2.92E+01	1.45E+02	4.61E+02	9.58E-01	4.24E-01	7.84E+00
2	2.51E+04	7.33E+02	2.12E+00	1.23E+00	2.14E+01	1.79E+02	4.06E+02	9.67E-01	4.86E-01	8.37E+00
2	2.87E+04	7.41E+02	2.12E+00	1.08E+00	1.91E+01	1.91E+02	4.57E+02	9.62E-01	3.84E-01	8.90E+00
4	3.09E+04	7.94E+02	1.48E+00	1.43E+00	2.04E+01	1.98E+02	5.24E+02	9.57E-01	4.78E-01	8.15E+00
3	2.67E+04	7.41E+02	1.92E+00	1.27E+00	2.06E+01	1.84E+02	4.69E+02	9.62E-01	4.70E-01	7.99E+00
Maize leaf disease dataset										
4	7.10E+01	3.85E+01	1.88E+00	1.69E+00	2.09E+01	9.51E+00	5.19E+02	9.46E-01	3.89E-01	9.75E+00
3	6.50E+04	1.02E+03	1.00E+00	1.01E+00	1.60E+01	2.88E+02	6.81E+02	9.08E-01	2.15E-01	1.27E+01
2	5.49E+04	1.24E+03	1.00E+00	1.19E+00	2.78E+01	2.64E+02	5.90E+02	9.36E-01	2.66E-01	1.20E+01
1	4.86E+04	1.44E+03	1.00E+00	1.35E+00	4.28E+01	2.49E+02	1.01E+03	8.57E-01	2.26E-01	1.21E+01
1	3.68E+04	9.66E+02	1.00E+00	1.78E+00	2.54E+01	2.16E+02	4.32E+02	9.10E-01	3.41E-01	1.07E+01

Figure 3: Sample Data Set

Each record in figure 3 contains 10 features such as area(f1), perimeter(f2), aspectratio(f3), rectangularity(f4), circularity(f5), equidiameter(f6), contrast(f7), correlation(f8), inverse difference moments(f9), and entropy(f10). These feature are utilized to evaluate the performance of the proposed method. The training or testing process of paddy and maize leave disease are performed separately.

B. Preprocessing

(i) Data regularization

Healthy leaves feature values ranges differ from diseased leaves features. So, it is essential to normalize the variations. So, this phase uses Z-score normalization to regularize the variations in the sample data.

$$Z-Score = \frac{a_i-\mu}{\sigma}, \qquad i = 1, \ldots.. N \qquad (1)$$

The mathematical derivation of the z-score normalization is given in eq(1). It is used to regularise the variations in the plant leave disease-related feature values. The variable a_i denotes each feature value. The symbol μ indicates the mean of sample data, and the σ denotes the standard deviation values.

(ii) Testing phase

Software testing is one of the essential steps in any application. It helps to improve the quality and performance of the model. It identifies the shortcomings in the software before launching it to users. But, this step needs to be addressed by most of the researchers. It may lead to produce an inefficient product. This study addressed these issues using software testing methods, including input shape verification and missing elements regularization techniques at the preprocessing level. This testing has been done with the help of linear regression and K-nearest neighbouring (LR-KNN) methods. These two models are combined to verify the data shape and data leakage of the input and predicted samples (It evaluates whether both data are equal or not). Suppose this LR-KNN detects any variations in the output samples; it does not allow the data to train the classier. This testing feature ensures the input data before training the classification model.

C. Feature selection

Plant leave disease classification models perform poorly due to overfitting issues by training with irrelevant feature information. These issues address the model fitting issues with the help of the Hilbert Schmidt Independence Criteria Lasso (HSICL) technique. It performs well on high and low-dimensional feature samples. Therefore, the leave disease classification approach uses the HSICL method to choose more significant features from the actual plant leave disease feature sets. These elected significant features support improving overall classification performance. The step-by-step flow of the HSICL-based features optimization is given as follows,

$HSICL: \min_{\alpha} \frac{1}{2} \sum_{NN,m=1}^{0} \alpha_{NN}\, \alpha_m HSICL(f_{NN}, f_m) - \sum_{NN,m=1}^{0} \alpha_{NN}\, HSICL\left(f_{NN,C}\right) + \lambda \|\alpha\|_1, \alpha_1, \dots \dots, \alpha_n > 0$ (2)

$HSICL: \min_{\alpha} \frac{1}{2} \left\| \overline{L} - \sum_{NN,m=1}^{0} \alpha_{NN}\, \overline{K}^{(NN)} \right\|_F^2 + \lambda \|\alpha\|_1, \alpha_1, \dots \dots, \alpha_n > 0$ (3)

Feature score is computed for each feature in the feature vectors using eq(2). The simplified form of the HSICL is given in eq(3) to compute the feature score. Once the feature score is computed, the top seven (5) features are selected based on their higher relatedness score values. In this study, paddy and Maize leaves infections and leaves healthiness-related features are considered. Kernel-based independence measures $(HSICL\left(f_{NN,C}\right) = tr(\overline{K}^{(NN)}\overline{L}))$ called empirical HSICL. The $tr(\ )$ method traces the observed HSICL values, and the notation λ indicates the regularization parameter. The input and output-centred gram matrices of Maize and paddy leave disease features are represented as $\overline{K}^{(N.N.)} = \Gamma K^{NN}\Gamma$ and $\overline{L} = \Gamma L \Gamma$. The gram matrices are computed as $K_{i,j}^{NN} = K(u_{NN,i}, u_{NN,j})$ and $L_{i,j} = L(c_i, c_j)$. The kernel functions are $K(u, u')$ and $L(c, c')$. The centring matrices are $\Gamma = I_0 - \frac{1}{0} 1_0 1_0^T$, and the variable I_0 indicates the 0-dimensional identity matrix(it contains paddy or Maize leave disease-related features). The value 1_0 indicates the m-dimensional vector with all once, and the notation $\|\ \ \|$represents the l_1-norm. The HSICL method uses the Gaussian kernel, which takes 7 neighbours to compute the score.

Table 1: HSICL-based Feature selection results for paddy and Maize leaves disease dataset

Samples	**Total Number of Features**	**Number of Selected Features**	**Selected Feature Combinations**
Paddy leaves	14	Top 5	f13, f14, f11, f9, and f1.
Maize leaves	10	Top 5	f4,f7, f8, f10, and f1

Table 1 contains Feature selection results using the HSICL method for the paddy, and Maize leaves disease dataset. The paddy leaves dataset contains 14 features, and the selected feature combinations are f13, f14, f11, f9, and f1. The Maize leaves dataset contains 10 features, and the selected feature combinations are f4, f7, f8, f10, and f1. Each feature's details are linked in the data sources part. The top 5 scored features are selected based on the maximum accuracy obtained by the WOANN classifier. The selected features are used as input to the WOANN classifier to predict the leaf disease.

D. Whale Optimized Artificial Neural Network (WOANN) Model

Parameter selection using Whale optimizer

The unusual hunting behaviour of humpback whales is considered the key motivating idea of these whales, which can be defined as a bubble net feeding technique. The hunting behaviours are converted as mathematical derivations to solve many optimization problems.

Searching for pray(SFP)

The SFP phase is used for global search problems. The WOA initiates the search process based on some solutions that are selected randomly.

$$\vec{D} = \left|\vec{C}.X_{rand} - \vec{X}\right| \quad (4)$$

$\vec{A}$ is defined as a random variable, and the values of the random variables are between -1 to 1. The WOA performs a global search when $\left|\vec{A}\right| > 1$.

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \quad (5)$$

Eq (5) expresses the mathematical form of the WOA's global search behaviours. The $\vec{D}$ defines the distance between the random position values (X_{rand}), a product of coefficient vector($\vec{C}$) with actual position($\vec{X}$), and | |denotes the absolute value, which performs element-by-element multiplication. The search agent updates their positions randomly for each iteration by selecting a search agent from obtained positions. The random search agent is selected when the value of $|\vec{A}|$ is > 1. The parameter range starts from 2 to 0. The mathematical derivations of the SFP are expressed in this phase.

Encircle the pray

$$D = \left|C\overrightarrow{X^*}(t) - X(t)\right| \quad (6)$$

$$X(t+1) = \overrightarrow{X^*}(t) - \vec{A}.\vec{D} \quad (7)$$

Suppose the optimal candidate solution is objective prey, eq(7) is used. It expresses the mathematical form of encircling the prey. The notation $\vec{A}$ and C is considered as the coefficient vectors. The r denotes the current position of the iteration, and the $\overrightarrow{X^*}$ denotes the position vector of the current optimal solution. The position vector is represented as $\vec{X}$.

$$\vec{A} = 2\,\vec{a}.\vec{r} - \vec{a} \quad (8)$$

$$\vec{C} = 2.\vec{r} \quad (9)$$

The eq(8) and eq(9) are used to evaluate the two coefficient vectors ($\vec{A}$ and $\vec{C}$). A value$\vec{a}$ can be chosen from 2 to 0 for each iteration, and the random vector($\vec{r}$) interval ranges [0,1].

Bubble net attacking phase

The humpback whales attack the prey using the bubble net attack method. This attacking phase contains two methods such as (1) the shrinking encircling method and (2) the spiral updating position method.

(1) The shrinking methods allow us to decrease the value of $\vec{a}$n in eq(8), and the value of $\vec{A}$ is randomly chosen from the intervals $[-a, a]$ such that a can be reduced from 2 to 0 during the iteration. Assumes that $\vec{A}$ has random values in the intervals $[-1,1]$.

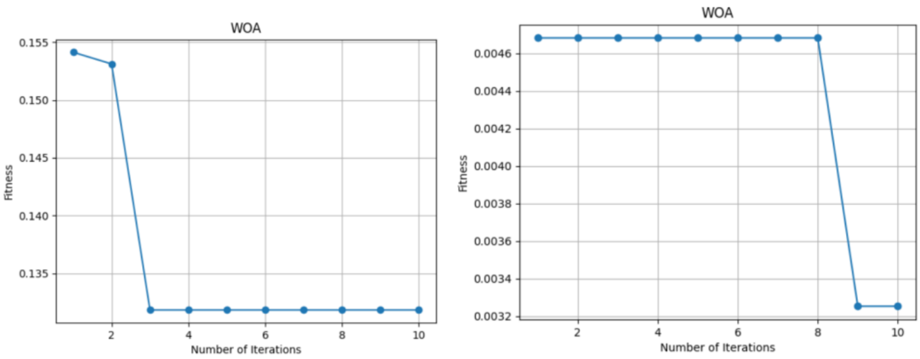
(2) The spiral method evaluates the position of the whale and the prey using the eq(10). The distance of ith whale to prey is defined in $\overrightarrow{D'}$ using the eq(11). The variable b is a constant value, and the l denotes the random number in the interval [-1,1]. The notation '.' Indicates the element-wise multiplication.

$$\vec{X}(t+1) = \overrightarrow{D'}.e^{b.i}\cos(2\pi l) + \overrightarrow{X^*}(t) \quad (10)$$

$$\overrightarrow{D'} = \left|\overrightarrow{X^*}(t) - X(t)\right| \quad (11)$$

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \vec{A}.\vec{D} & if\ p < 0.5 \\ \overrightarrow{D'}.e^{bi}\cos(2\pi l) + \overrightarrow{X^*}(t) & if\ p \geq 0.5 \end{cases} \quad (12)$$

During the optimization phase, using eq(12), the humpback whales swim around their prey in a shrinking circle with a probability of 0.5 % to select between a spiral model to update the position of whales or the shrinking encircling method. The value of the variable p is the random value between the interval [0,1].



a) b)

Figure 4: Performance of WOA for paddy leaves dataset and maize leaves dataset

Figure 4 shows how close a given solution is to the optimum solution of the desired problem. This optimum solution of WOA is used to optimize the parameter values of the ANN classifier. The WOA use 10 particles per iteration as the population size, and 10 iterations are used as stopping criteria to get the optimum value (Converged solution). The optimized parameters and input features are used to train the ANN classifier to detect the plant leaves diseased and healthy classes.

Artificial Neural Network model

The ANN model has a fault tolerance feature. Sometimes healthy and infected leaves have similar or extortion features due to similar feature values for some infections. So, this study uses an ANN classifier to classify plant leaves diseases. An ANN classification model contains a large number of artificial neurons. It termed units arranged in sequential layers (S.L.). The SL is formed using different layers, including the input layer(I.L.), hidden layers(H.L.), and output layers(O.L.). I.L. receives the inputs in numerous formats provided by the developers. H.L. performs all the calculations to find hidden features. It presents between I.L. and O.L. The inputs go through a series of transformations using the H.L. The classification model's final result is produced in this layer. The ANN takes input and computes the weighted sum of the inputs and bias.

$$\sum_{i=1}^{n} W_i * X_i + b \quad (1)$$

The eq(1) represents the transformer function of the ANN model. The weighted total is given as input to the activation function(A.F.). The A.F. decides whether or not the given input neuron is taken to train the model. If an input feature satisfies the output state activation condition, the input features are considered for training the model.

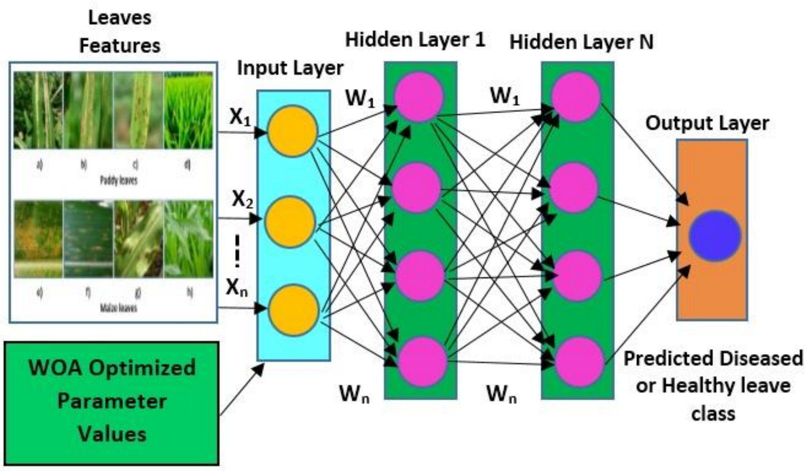


Figure 5: WOA-optimized ANN Architecture

Figure 5 illustrates the architecture of the WOA-optimized ANN classifier. The WOA-optimized parameters are used to train the ANN model. The WOANN model is designed to a sequence of layers including one I.L., two H.L. and one O.L. Two dense layers are added to perform the hidden layer's functionalities. This layer uses 50 hidden units and follows the uniform method to initialize the kernel. The relu activation function is used in I.L. and H.L. The input dimension is declared 7. A dense layer is used in O.L. The O.L. uses the sigmoid activation to decide the training decisions of input features, and this layer uses 1 input unit to produce the output. It uses Stochastic gradient descent optimization techniques to optimize the network weight during the model training and backpropagation stage, and the categorical cross entropy method is applied as the loss function. The performance analysis of the WOANN model is given in the subsequent section.

2. Result and Analysis

This section investigates the WOANN model's performance detecting Maize and paddy leaf disease. This model is implemented and evaluated the performance in Python. It imports the pandas and numpy library functions to perform this leaf disease detection. This open-source software provides a flexible environment for designing deep learning models and their functionalities.

Table 2: Parameter values used by the WOANN model

S.No	Parameter	Value
1	Hidden units	10
2	Activation function	Relu
3	Regularization value	0.01
4	Learning rate	0.01
5	Epochs	5
6	Batch size	Obtained from WOA's curves.

Table 2 contains the parameter values used by the WOANN model for the plant leave disease prediction. The performance of WOANN is compared with existing plant leaves disease models to determine the model's excellence. The performance comparison is made with Optimized classification models and some recent performance-wise best deep learning-based plant leaves disease detection models, including WG-MARNet [23], VGG-16[24], CNN [25], ANN[26], and FSO SVM[29]. It evaluates the model based on performance analysis metrics such as accuracy, recall, precision, and f-score.

Table 3: Paddy and Maize leaves disease detection performance of WOANN model

Iterations	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)	
Paddy Leaf Disease					
1	99.02	**99.20**	**99.13**	99.10	
2	99.12	99.11	99.06	**99.12**	
3	99.08	99.07	99.04	99.03	
4	**99.13**	99.06	99.11	99.09	
Maize Leaf Disease					
1	99.04	99.03	**99.23**	99.11	

2	99.13	99.10	99.13	**99.24**	
3	**99.35**	**99.24**	99.06	99.12	
4	99.18	99.16	99.22	99.08	

Table 3 contains the overall performance of the WOANN model for paddy and maize leaf disease detection. It clearly shows that the WOANN model obtained a maximum of 99.13 % and 99.35 % accuracy rates for detecting paddy and maize leaf disease.

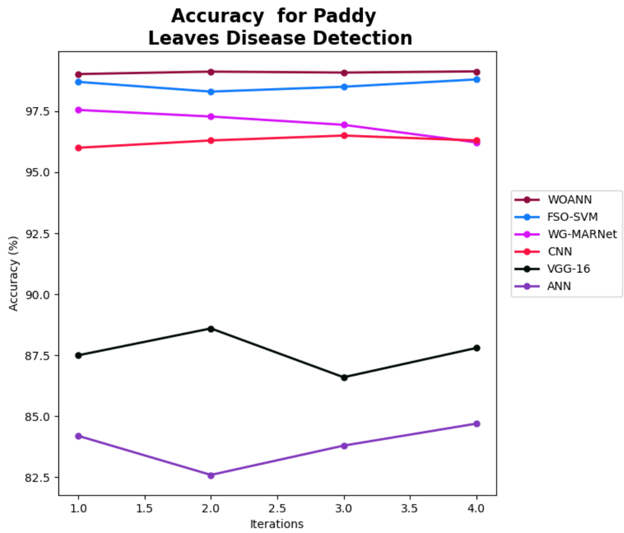


Figure 6: Paddy leaves disease detection accuracy comparison

Figure 6 illustrates the accuracy rate achieved by WOANN, FAOSVM, WG-MARNet, CNN, VGG-16, and ANN classifiers for the paddy leaves disease features dataset. It shows that the WOANN model's increased the accuracy rate to 99.13%. It is maximum than comparison methods.

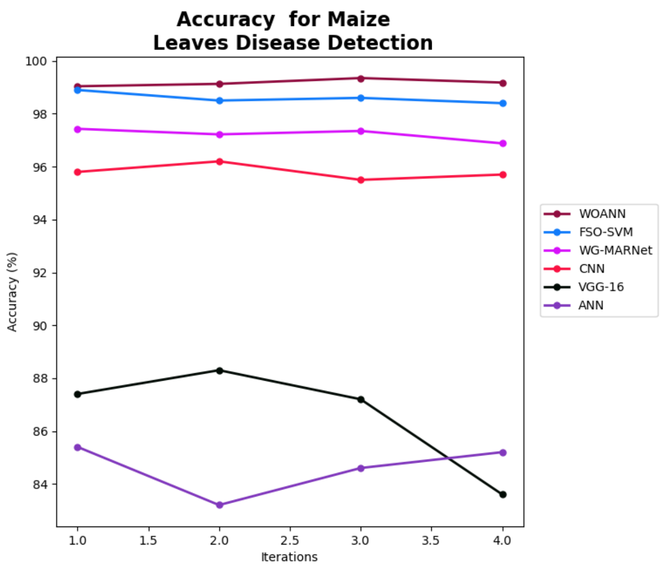


Figure 7: Maize leaves disease detection accuracy comparison

Figure 7 depicts the WOANN, FAOSVM, WG-MARNet, CNN, VGG-16, and ANN classifiers obtained accuracy rate comparison for the Maize leaves disease features dataset. It shows that the WOANN model's increased the accuracy rate to 99.35%. It is maximum than comparison methods.

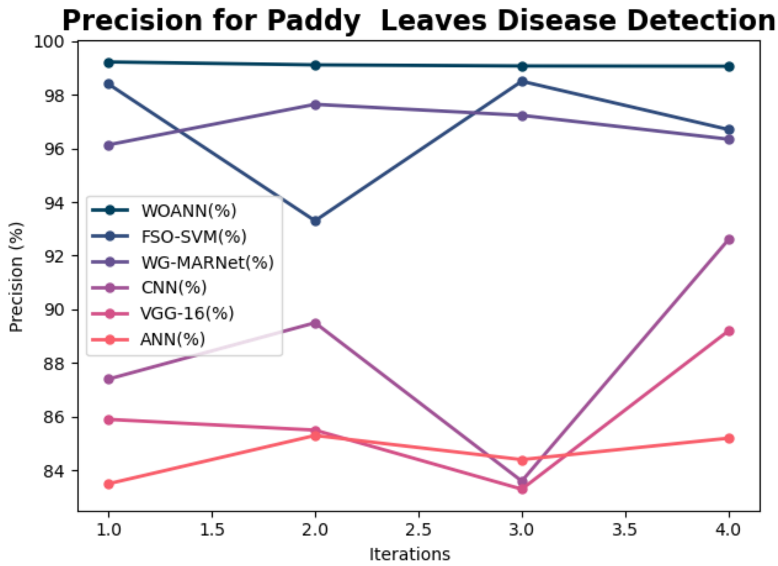


Figure 8: Paddy leaves disease detection precision comparison

Figure 8 illustrates the precision rate achieved by WOANN, FAOSVM, WG-MARNet, CNN, VGG-16, and ANN classifiers for the paddy leaves disease features dataset. It shows that the WOANN model's increased the precision rate to 99.20%. It is maximum than comparison methods.

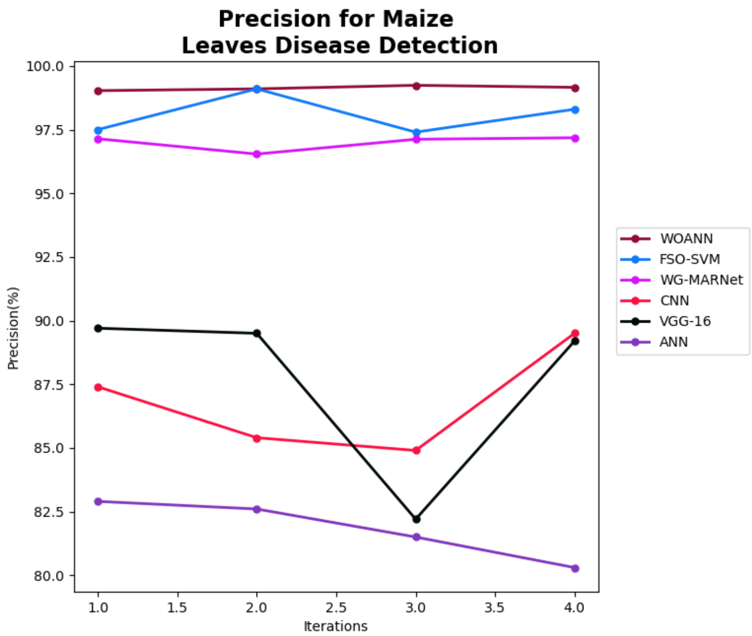


Figure 9: Maize leaves disease detection precision comparison

Figure 9 depicts the WOANN, FAOSVM, WG-MARNet, CNN, VGG-16, and ANN classifiers obtained precision rate comparison for the Maize leaves disease features dataset. It shows that the WOANN model's increased the precision rate to 99.24%. It is maximum than comparison methods.

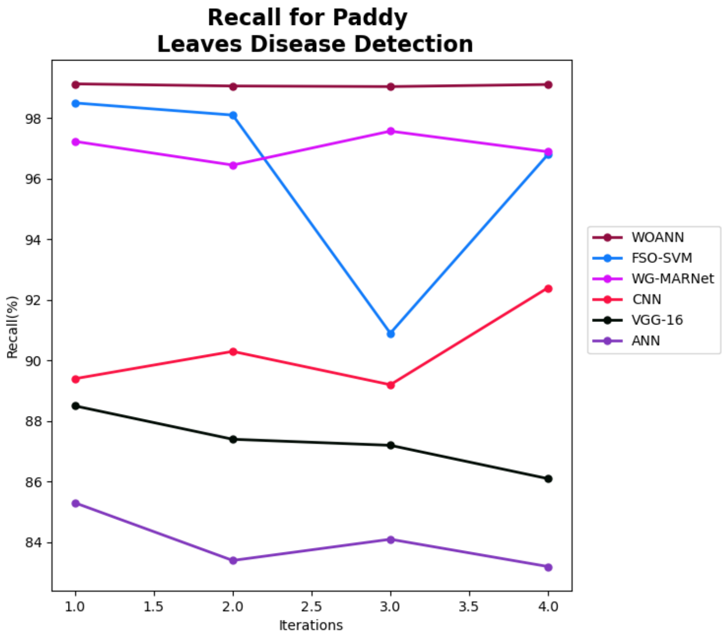


Figure 10: Paddy leaves disease detection recall comparison

Figure 10 illustrates the recall rate achieved by WOANN, FAOSVM, WG-MARNet, CNN, VGG-16, and ANN classifiers for the paddy leaves disease features dataset. It shows that the WOANN model's increased the recall rate to 99.13%. It is maximum than comparison methods.

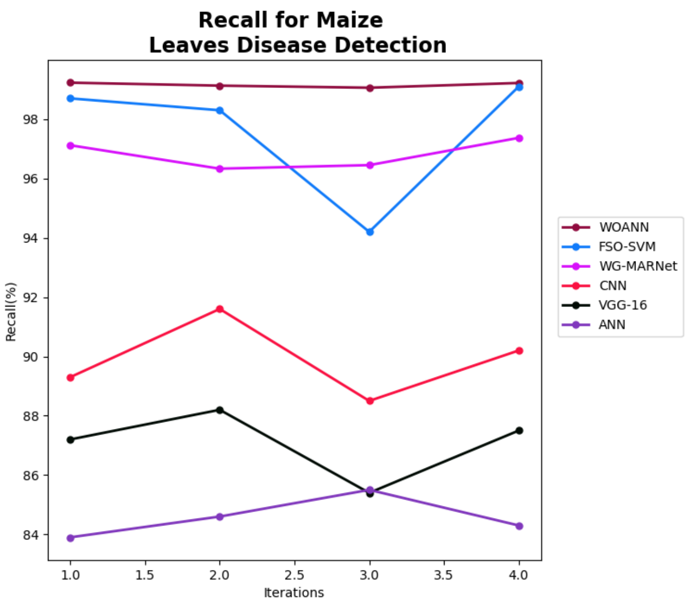


Figure 11: Maize leaves disease detection recall comparison

Figure 11 depicts the WOANN, FAOSVM, WG-MARNet, CNN, VGG-16, and ANN classifiers obtained recall rate comparison for Maize leave disease features dataset. It shows that the WOANN model's increased the recall rate to 99.23%. It is maximum than comparison methods.

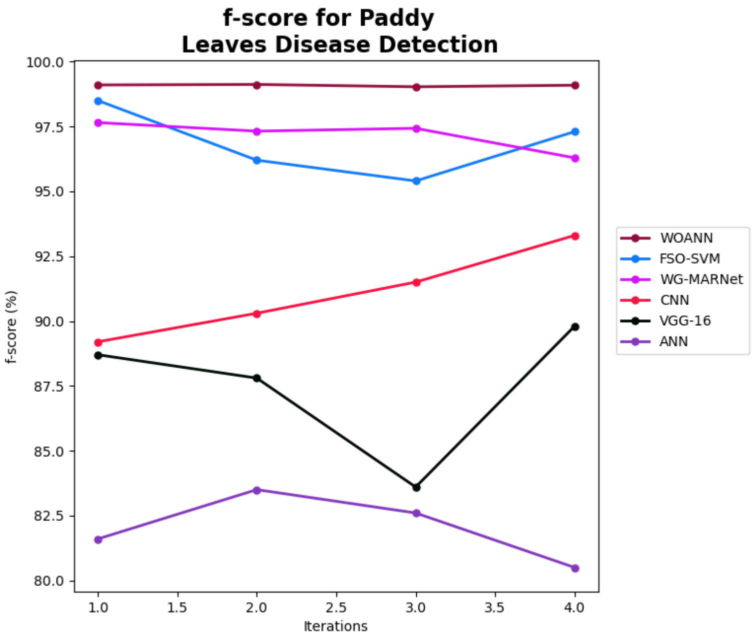


Figure 12: Paddy leaves disease detection F-score comparison

Figure 12 illustrates the f-score rate achieved by WOANN, FAOSVM, WG-MARNet, CNN, VGG-16, and ANN classifier for paddy leave disease features dataset. It shows that the WOANN model's increased the f-score rate to 99.12%. It is maximum than comparison methods.

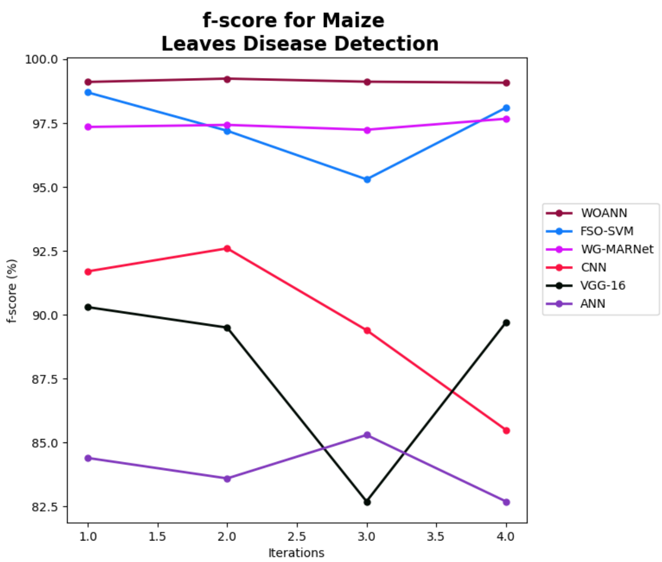


Figure 13: Maize leaves disease detection F-score comparison

Figure 13 depicts the WOANN, FAOSVM, WG-MARNet, CNN, VGG-16, and ANN classifiers obtained f-score rate comparison for Maize leave disease features dataset. It shows that the WOANN model's increased the f-score rate to 99.24%. It is maximum than comparison methods.

The performance comparison analysis shows that the WOANN gives a better accuracy rate for maize datasets than paddy datasets. The overall performance analysis indicates that the WOANN outperforms comparison classification methods for paddy and Maize leave disease datasets.

3. Conclusion

Thus, the study introduces the WOANN model-based paddy and maize leaf disease approach. The research aims to develop an improved leave disease detection model to improve accuracy and efficiency. This study introduces LR-KNN and WOANN models for data shape checking model during the preprocessing stage to ensure the completeness of input data and whale optimizer algorithm optimized ANN classifier improving the leave disease detection accuracy. This study also uses the HSICL method to reduce overfitting issues. The WOANN classifier obtained a maximum of 99.35% classification accuracy for the maize leaf dataset and 99.13% as the maximum accuracy rate for the paddy leaf dataset. The performance analysis proves that the WOANN-based approach outperforms comparison approaches. So, the study concludes that the WOANN achieve the research objective by improving the leave disease detection performance. Moreover, the whale optimizer is utilized to optimize the functionalities of the ANN classifier, but still, the WOANN model's performance is limited to reduce the overfitting issues, so the study is extended to overcome the overfitting issues by using a hybrid feature selection method.

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