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COCONUT TREE DISEASE CLASSIFICATION USING WHALE OPTIMIZATION ALGORITHM

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Abstract

Recent research in agriculture focuses on classifying agricultural plant diseases using images of their leaves. This will minimize the dependence on farmers to protect the plants. Coconut trees fall prey to a variety of pests and diseases due to fungi, bacteria, viruses and nematodes. Many researchers are increasingly turning to metaheuristic algorithms because of their success in finding optimum solutions in solving real-world issues. This paper proposes a unique nature- inspired meta-heuristic optimization algorithm, referred to as Whale Optimization algorithm (WOA) based Deep Neural network to classify the Coconut tree diseases.

Keywords: Classification, Coconut tree, disease, Whale Optimization and DNN.

1. Introduction

The agriculture sector may be considered because the backbone for any developing economy. To gain the most yield from the plants, it's far required that farmers must be supplied with the best technologies and methodologies. Coconut is a palm plantation essential for its numerous makes use of from its fruit to trunk. India is the third biggest producer of coconut and its by-products in the world. The southern states of India make contributions a majority of the production in India. Any diseases affecting the yield of the coconut plantation finally affects the related industries and the livelihood of the families who depend on the coconut economy.

According to Piyush Singh, coconut trees were affected due to pest infection stem bleeding and leaf blight diseases [1]. A total of 1564 images were captured from the farms of kayar village, Tamilnadu. Using k-means for segmentation and convolutional neural network as a classifier, he was able to achieve a validation accuracy of 96.94%. The paper further describes the various architectures of CNN and compares the performance of each of them in detail.

Coconut is a palm plantation vital for its various uses from its fruit to trunk. India is the third-largest producer of coconut and its by-products in the world [2]. The southern states of India contribute a majority of the production in the country. Any disease affecting the yield of the coconut plantation eventually affects the related industries and the livelihood of the families who depend on the coconut economy [3].

P. Balamurugan and R. Rajesh [4] deals with the classification of coconut tree leaves which are affected by one of the diseases named as 'leaf rot'. They used Neural Network Based System for the Classification of Leaf Rot Disease in Cocos Nucifera Tree Leaves. Abraham Chandy [5] proposed a precision agriculture technique to detect various pests in coconut trees with the help of NVIDIA Tegra System on Chip (SoC) along with a camera interfaced drone. The drone flies across the coconut farm and captures the images and processes the data using deep learning algorithm to identify the unhealthy and pest affected trees. The deep learning algorithm uses a set of sample pest database.

Dirami, Ahmed, et al [6] employed the Thresholding segmentation (THS), techniques to segment the images before going for the classification process. Alshawwa et.al.,[7] proposed the expert System which was produced to help farmers in diagnosing many of the coconut diseases such as: Bud Rot, Leaf Rot, Stem Bleeding, Tanjore wilt and Root (wilt). Major diseases and Pests affecting coconut trees are given below and it is shown from Fig.1 to Fig.10.

1.Ganoderma – basal stem rot (BSR)
2.Root Wilt Disease (RWD)
3.Bud rot
4.Leaf Blight
5.Stem bleeding disease
6.Leaf rot
7.Rhinoceros beetle
8.Red palm weevil
9.Black-headed caterpillar
10.Coconut Eriophyid Mite and Termite


Fig.1. Ganoderma-basal stem rot


Fig.2. Root Wilt Disease


Fig.3. Bud rot

Fig.4.Leaf Blight

Fig.5. Stem bleeding disease

Fig.6. Leaf rot

Fig.7.Rhinoceros beetle

Fig.8. Red palm weevil

Fig.9.Black-headed caterpillar

Fig,10. Coconut Eriophyid Mite and Termite

A new metaheuristic algorithm with naturalistic inspiration was discussed by Mirjalili et al. [8] and is based on how humpback whales hunt using bubble nets. The Whale Optimization Algorithm (WOA) imitates humpback whales' hunting techniques. Whales are elegant animals and they are regarded as the world's largest mammals. Up to 30 metres long and 180 tonnes in weight, a mature whale can grow. This huge mammal has seven primary species, including the killer, Minke, Sei, humpback, right, finback, and blue. Most people think of whales as predators. Since they must breathe ocean surface air, they are unable to sleep. Indeed, the other half of the brain is asleep. The fascinating thing about whales is that they are thought to be very intelligent, feeling animals.

The necessary data set is gathered in this study to identify the signs of diseases and pest infestations affecting coconut plants. The median filter is used to reduce the undesirable noise that was present in the obtained image. The diseased area in the image is segmented using the Fuzzy Rough C-Means (FRCM) clustering algorithm. Coconut tree diseases are categorized using a Deep Neural Network based Whale Optimization Algorithm (WOA).

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2 Whale Optimization Algorithm (WOA)

This huge mammal has seven primary species, including the killer, Minke, Sei, humpback, right, finback, and blue. Since they must breathe ocean surface air, they are unable to sleep. Indeed, the other half of the brain is asleep. The fascinating thing about whales is that they are thought to be very intelligent, feeling animals. According to Hof and Van Der Gucht [9], spindle cells are a type of common cell that whales share with human beings in specific regions of their brains. These cells are responsible for judgment, emotions, and social behaviors in humans.

Humpback whales prefer to hunt school of krill or small fishes close to the surface. It has been observed that this foraging is done by creating distinctive bubbles along a circle or '9'shaped path as shown in Fig.11. It is worth mentioning here that bubble-net feeding is a unique behavior that can only be observed in humpback whales. In this work the spiral bubble-net feeding maneuver is mathematically modeled in order to perform optimization.

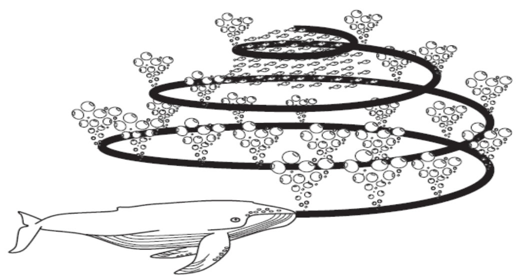

Fig. 11. Bubble-net feeding behavior of humpback whales.

The steps involved in WOA are as follows,

Step 1: Initialization

Initially, random values are assigned to weights of hidden neurons in hidden layers, which are utilized to start the optimization process.

Step 2: The fitness function has been estimated.

The goal of WOA is to lower the Mean square error (MSE), which is determined using the equation below.

$$MSE=\sum_{i=1}^{n}\frac{(x_i-y_i)^2}{n} \quad (1)$$

Where input data is denoted as x_i, the output data is denoted as y_i and the number of iterations is denoted as n.

Step 3: The location to be updated.

The equations below determine the modernized process,

$$\vec{U}=\left|\vec{\gamma}\cdot\vec{p}_{best}(t_{it})-\vec{p}_{best}(t_{it})\right| \quad (2)$$

$$\vec{p}(t_{it}+1)=\vec{p}_{best}(t_{it})-\vec{\omega}.\,\vec{U} \tag{3}$$

Where the current iteration is indicated as t_{it}, the coefficient vector is indicated as $\vec{\gamma}$, the position vector for best description is denoted as $\vec{p}_{best}$ and the existing position vector is denoted as $\vec{p}$.

The vectors $\vec{\omega}$ *and* $\vec{\gamma}$, which are expressed as,

$$\vec{\omega}=2\vec{\mu}.\vec{r}_i-\vec{\mu} \tag{4}$$

$$\vec{\gamma}=2.\vec{r} \tag{5}$$

Here, $\vec{\mu}$ is minimized from 2 to 0 and $\vec{r}_i$ indicates the unsystematic vector in $(0,1)$.

$$\vec{p}(t+1)=\vec{U}.\,e^{\eta\varphi}.\,\cos(2\pi\varphi)+\vec{p}_{best}(t) \tag{6}$$

$$\vec{p}(t+1)=\begin{cases}\vec{p}_{best}(i)-\vec{\omega}.\,\vec{U} & \text{if } R<0.5\\ \vec{U}.\,e^{\eta\varphi}.\ \cos(2\pi k)+\vec{p}_{best}(t) & \text{if } R\geq 0.5\end{cases}$$

$$\vec{U}=\left|\vec{\gamma}.\vec{p}_{rand}-\vec{p}\right| \tag{7}$$

$$\vec{p}(t+1)=\vec{p}_{rand}-\vec{\omega}.\vec{U} \tag{8}$$

Where the random position vector is denoted as $\vec{p}_{rand}$. The search mediators are commonly utilized in a recursive process to modernize their position by employing the best search mediator.

3 Classification using WOA-DNN

The framework of DNN essentially contains three primary components which include input layer, output layer and hidden layers. The proposed architecture of DNN is shown in Fig.12. By considering the effort of preference weight fitness, the DNN is designed with two hidden layers for perfectly learning the mapping relation between the input and output data. In the training phase, by using the WOA-DNN iteratively updates the weight of the nodes in the hidden layers. Due to the increase in the training iterations, this neural network continually fits the labelled training data's decision boundary. To enhance the training speed of the DNN and the classification accuracy, two hidden layers are constructed. In the hidden layer the total number of nodes is evaluated by using Eqn. (20).

$$N=\sqrt{a+b}+c \tag{9}$$

where, the number of input layer nodes is given as a, the number of output layer nodes is given as b, the number of hidden layer nodes is represented as n and a constant value between [1,10] is notated as c. For

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enabling the non-linear fitness ability an activation function is added in the hidden layer of DNN. We have used the softmax as an activation function and it is given as,

$$S(y)_i = \frac{\exp(y_i)}{\sum_{j=1}^{n} \exp(y_i)} \tag{10}$$

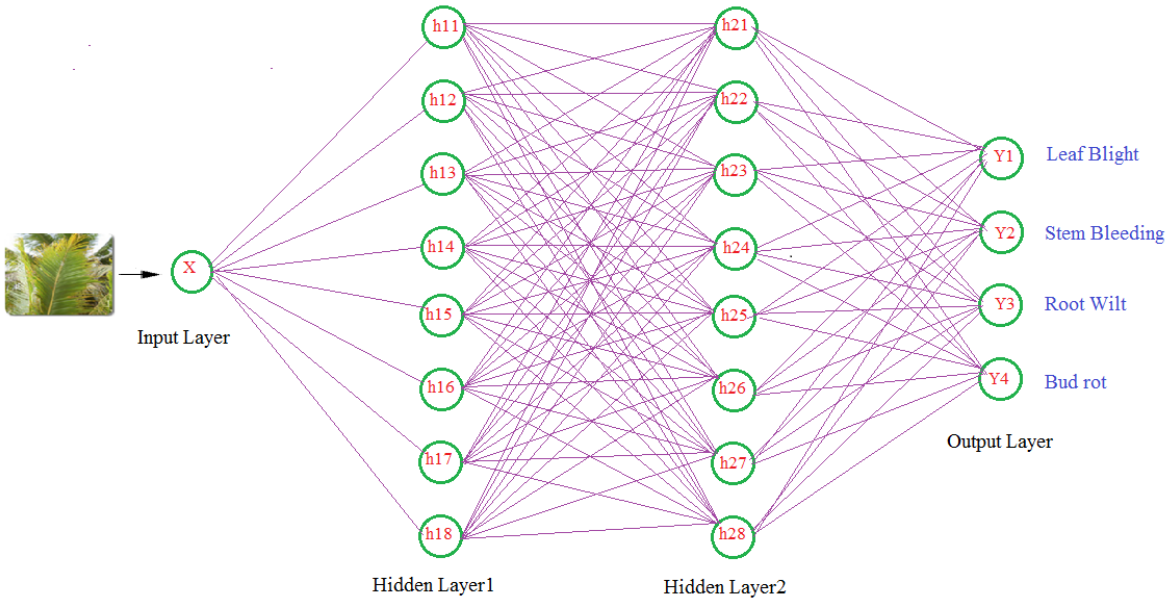

Fig.12. Architecture of DNN with two hidden layers.

The input data of the network is termed as x and it is activated by the mapping function M_f.

$$M_f = sigm\ (\omega_i X + \beta_i) \tag{11}$$

where, x and b represents the weight matrix and the bias between the output layer and the hidden layer respectively. To cause the representation space of the hidden neurons to align with human knowledge, we introduce another supervised loss function for DNN. In this case, we are utilizing the information contained in the data sample labels, which represent the human concepts. The loss form can be computed as

$$S(w_S, b_S; x, 1) = \frac{1}{2m} \sum_{j=1}^{m} \left\| h_i(w_S, b_S; x) - l_j \right\|^2 \tag{12}$$

where W_s and b_s are the subsets of biases and m is the number of neurons in the hidden layer. Cross entropy is used as the loss function of DNN as the preparation for training and testing. The use of cross entropy losses greatly improved the performance of the sigmoid and softmax output models. The cross entropy loss is evaluated by the Eq. (16).

$$C_E = \frac{1}{N} \sum_{K=1}^{N} \left[Y_k log \hat{Y}_k + (1 - Y_k) \log (1 - \hat{Y}_k) \right] \tag{13}$$

where, n represents the training sample quantity, Y_k indicates the k^{th} actual output of training set, Y^k is the k^{th} expected output of testing set. WOA are used to find the optimal weight selection of DNN network. By updating the values, these algorithms efforts the fitness value to shift towards the best solution. After that, the new solutions and the old solutions are compared and for the next iteration only the best solutions are considered. The adjusted solution is compared with the previous solution. If the previous one is improved it will replace the previous solution else it will retain the previous solution. The process is repeated from until the termination criteria are achieved.

4 Results and Discussion

The sample images shown in Figs 13(a), 14(a) and 15(a) namely leaf blight and stem bleeding are given as input to wiener filter. The pre processed outputs are presented in Figs.13(b), 14(b) and 15(b). The pre processed outputs are given as input to the Fuzzy Rough C-Means (FRCM) segmentation algorithms**.** The segmentation results of the image processing algorithm are shown in Figs.13(c), 14(c) and 15(c). The results indicate that the FRCM segmentation algorithm performed better for segmenting the regions. FRCM segmentation carries out its function to segment relevant regions in every category without problems. For example, stem bled regions and sections with holes are properly segmented.



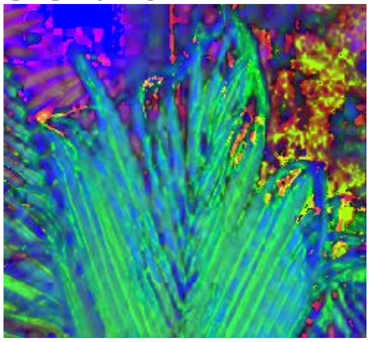

Fig.13(a) Leaf Blight **Fig.13(b) Pre processed output** **Fig.13(c) Segmented output**



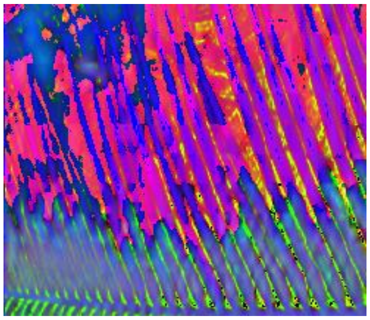

Fig.14(a) Leaf Blight **Fig.14(b) Pre processed output** **Fig.14(c) Segmented output**



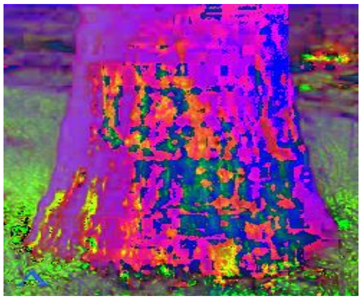

Fig.15(a) Stem Bleeding **Fig.15(b) Pre processed output** **Fig.15(c) Segmented output**

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400 images were used for classification of four coconut plant diseases namely Leaf blight, Stem bleeding, Root wilt disease and Bud rot**.** Table 1 gives the accuracy of proposed classification method. Classification Performance Metrics are tabulated in Table 2.

Table 1. Classification Accuracy

S.No	**Disease**	**Samples taken**	**WOA-DNN Rightly detected**
1.	Leaf blight	100	95
2.	Stem bleeding	100	96
3.	Root Wilt Disease	100	94
4.	Bud rot	100	96
	Total	400	381

Table 2. Classification Performance Metrics.

S.No	Name of the Disease	Samples	Precision = True positives/(True positives+False Positives)	Recall (Sensitivity) = True positives / (True positives +False Negatives)	F-Score= (2*Precision* Recall) /(Precision + Recall)	Specificity= True Negatives/ (True Negatives+ False Positives)
			WOA-DNN	WOA-DNN	WOA-DNN	WOA-DNN
1	Leaf blight	100	0.86	0.89	0.90	0.90
2	Stem bleeding	100	0.87	0.87	0.89	0.89
3	Root Wilt Disease	100	0.90	0.89	0.87	0.91
4	Bud rot	100	0.90	0.87	0.90	0.90

5 Conclusion

Automated Coconut plant disease detection is indeed a blessing to farmers. The proposed system uses FRCM clustering for segmentation and Whales Optimization Algorithm based Deep Neural Network for classification purposes. Based on the experimental results, the efficiency of the proposed system can be mightily seen as accuracy shoots up to 95.25%. The current system works on a single digitized color image of a leaf as the input. This may be extended and in future, the system might work on a batch of images that consider all the parts of a plant for better output prediction.

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