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Use of White Shark Optimization for Improving the Performance of Convolution Neural Network in Classification of Infected Citrus

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Abstract

Citrus plant diseases are major causes of reduction in the production of citrus fruits and their usage. Early detection of the onset of the diseases is very important to curb and reduce its spread. A number of researches have been done on the detection and classification of the diseases, most of which have identified poor labelling of symptoms which result into improper classification. Some researchers have also experimented on the effectiveness of convolution neural network and other deep learning techniques, most of which results into a faster convergence but suffers from low accuracy, computational overhead and overfitting as fundamental issues. To reduce the effects of overfitting, this research developed a White Shark Optimization-Convolution Neural Network (WSO-CNN) technique to address the aforementioned problem by introducing a regularization strategy via feature selection which selects more useful and distinguishing features for classification. As a result, the developed technique was able to detect and classify various types of citrus fruit diseases and label them accordingly with low false positive rate, high sensitivity, specificity, increased accuracy and reduced recognition time, based on all the experiments performed with the dataset used in the research. Hence WSOCNN performed better than CNN in classifying citrus plant disease having a reduced FPR of 3.57%, 8.34%, 3.89% and 9.00% for black spot, greasy spot, canker and healthy/non healthy dataset respectively.

***Keywords**:* optimization, deep learning, pattern recognition, classification

1. Introduction

Plant diseases can have a significant negative influence on the quality and quantity of agricultural products as well as the safety of food. Disease identification is crucial to ensuring the quality and quantity of produce as well as to minimize orchard damage. In severe cases, plant infections may completely kill the crop. A considerable annual loss of agricultural products is caused by plant diseases, which have a significant impact on crop productivity and output. Less product loss occurs when plant diseases are promptly controlled. Given the current environmental and meteorological conditions, the significance of precise and timely disease identification, which includes early blockage, cannot be stressed [1].

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Plant disease is a serious issue in agriculture. There are numerous pathogens that cause plant diseases. Manual inspection can sometimes lead to mistakes in the disease identification process across a large crop area. Conventional plant disease diagnosis by human experts is tiresome, capital intensive, and lacks the ability to detect diseases in real time [2]. Microelectronic devices have mostly been used to identify and monitor agricultural illnesses instead of direct observation. Accurate forecasting also needs a high level of experience. While the conventional approach to illness identification relies on professionals observing patients with their own eyes and necessitates ongoing surveillance, it also comes at a considerable expense for large farm plantations. However, an automated plant disease detection and diagnosis system are a necessity. An astounding application of image processing and computer vision is detecting fruit and plant diseases. Many methods have been proposed to address this issue, but deep learning has emerged as the favored option due to its amazing outcomes.

Computer vision and machine learning algorithms have made tremendous progress in the detection of plant diseases in recent years [3]. An advancement of machine learning is deep learning, in which CNN are a class of deep learning (DL), having the input, output and increased number of hidden layers. Greater accuracy is offered by multiple hidden layers than by shallow networks. Deep Networks, particularly convolutional neural networks (CNN), have achieved remarkable results in detection, precision and image classification with the advances in technology and computing power.

However, overfitting is a fundamental issue in Convolution Neural Network (CNN), in which models are prevented from generalizing well to fit observed data on training data, as well as unseen data on testing set. This has most often affected the accuracy of the system, resulting in high false positive rate [4]. CNN guarantees to perform better only with optimized feature subsets. This is what this research intends to address. WSO is used to adequately adjust the weights and learning rate of CNN in order to reduce the loss and improve the accuracy.

The core ideas and foundations of WSO are inspired by the behaviors of great white sharks, including their exceptional senses of hearing and smell while navigating and foraging. These aspects of behavior are mathematically modeled to accommodate a sufficiently adequate balance between exploration and exploitation of WSO and to assist search agents to explore and exploit each potential area of the search space in order to achieve optimization. The search agents of WSO randomly update their position in connection with best-so-far solutions, to eventually arrive at the optimal outcome. WSO has several advantages for global optimization problems, such as its flexibility to deal with different types of optimization problems. The mathematical algorithm for WSO makes it relevant to address various kinds of real world optimization problems, especially those of high dimensionality. The simplicity and robustness of WSO make it rapid and accurate to find the global solution to difficult optimization problems with high convergence speed [5]. The aim of this research is to develop an infected citrus fruit detection and classification system using White Shark Convolution Neural Network (WSO-CNN) Algorithm. The performance of the proposed model was evaluated in terms of sensitivity, specificity, false positive rate, accuracy and average recognition time.

2. Related Works

Machine learning and image processing techniques are the main expertise required to propose and develop efficient method for diagnosing and preventing infection in agricultural products.

Over the last 25 years, significant progress has been made in improving the consistency, accuracy, and precision of image-processing for recognizing and characterizing plant illnesses. It has been stated that over 1000 papers are expected each year due to the developing fields of computer vision and image processing [2].

Xinxing, Yi and Yaohui [6] proposed a deep learning-based algorithm for automated identification of five common types of citrus diseases in orchards. The proposed algorithm consisted of a detection network to detect the citrus fruit in the complicated background and a classification network to classify them into the corresponding types. The work considered several state-of-the-art network architectures for object detection and classification performance and evaluated on a dataset of 1524 images which were obtained from different orchards in distinct time intervals, scales, angles, and lighting conditions. The experimental results using YOLO-V4 for detection and EfficientNet model for classification the overall algorithm obtained the accuracy and F1 score of 0.890 and 0.872, respectively, likewise featuring high efficiency and precision.

Barman and Choudhury [7] proposed a transfer learning-based model which used deep convolutional neural networks for identifying and classifying citrus fruits diseases. The InceptionV3, ResNet50, VGG16 and VGG19 models are pre-trained model on a large dataset (ImageNet). Data augmentation was used and there was an improved accuracy of classification. The performance of the models were compared based on accuracy on the dataset; the results show that VGG19 got the highest accuracy, 99.89%. The experimental results show that transfer learning provides better prediction with minimal computational resources.

Jiang, Li and Safara, [2] proposed a method to detect infections in apple fruit and prevention of further infections using deep learning techniques. Deep neural network with different convolution layers and different number of neurons were examined and results evaluated in terms of accuracy, sensitivity, specificity and ROC curve, the superiority of the proposed method was demonstrated from the results.

Jackulin and Murugavalli, [1] conducted an extensive study on various type of machine learning and deep learning techniques for detection and recognition of plant diseases. The work summarized several techniques and made a comparative study between machine learning and deep learning techniques. By and large, noteworthy progress results have been noteworthy, even though the research identified several gaps that needs to be addressed and implemented for improved and effective techniques in the research domain.

Dahiya, Gulati and Gupta [3] employed different deep architectures plant leaves disease detection. The work used a plant village dataset of 20640 images which represents 15 class and 3 species namely pepper, potato, and tomato. Determination of the appropriate value of hyper parameter was done by varying number of epochs and learning rate. Eight different deep learning architectures were evaluated based on their performance. Analyzing GoogleNet, ResNet18, ResNet50, ResNet101, MobileNetv2, ShuffleNet, AlexNet, and SqueezNet reveals that ResNet50 & ResNet101 outperforms in detection accuracy while AlexNet and SqueezNet perform worse for 32 & 16 Mini batch sizes. Adam optimizer was compared with SGDM optimizer and the result shows that the performance of Adam optimizer was found better than SGDM optimizer. Also, the results suggest that 30 numbers of epochs are sufficient as it takes lesser time for training without any significant degradation in accuracy.

Alessandrini *et. al.* [8] presented an image dataset of grapevine leaves. The dataset holds grapevine leaves images belonging to two classes: unhealthy leaves acquired from plants affected by Esca disease and healthy leaves. The work further trained a simple CNN using the proposed dataset with augmentation and for three different pixel sizes (1280 ×720, 320 ×180, 80 ×45). To demonstrate how the dataset might be used for various target applications, several resolutions that were obtained by down sampling the source photos were taken into consideration. The CNN training, validation and testing was performed on the augmented dataset splitted ass 60% train, 15% validation and 25% test. Loss and accuracy achieved on training, validation and testing shows outstanding performance of the CNN model.

Sambasivam and Opiyo [9] presented a system for classification of Cassava plant disease. The work focused more on how to counter high-class imbalance discovered in the cassava dataset since the data was heavily biased towards CMD (Cassava Mosaic Disease) and CBSD (Cassava Brown Streak Virus Disease) classes. This was done so that the model can accurately predict underrepresented classes. SMOTE (Synthetic Minority Over-sampling Technique) and focal loss with deep convolutional neural networks CNN was used. The CNN was trained from scratch. The model performance showed promising results and the techniques achieve an accuracy score of over 93% with class weight. The work reported an increment of over 5% in accuracy and a log loss that dramatically reduced to 0.06% from over 20% when class-imbalanced rectification techniques coupled with data augmentation and large input image dimensions were used.

Belay *et. al,* [10] developed a chickpea disease detection model using deep learning techniques by combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) for feature extraction and Softmax for classification. In the work various image preprocessing stages such as image resizing, normalization, and noise filtering using a combination of Gaussian filter (GF) and Median filter (MF) were performed. Augmentation was done on the data to prevent overfitting. 8391 images were used to train and test the effectiveness of the developed model. 60% of the dataset was used for training, 20% of the dataset was used for testing and 20% was used for validation. The proposed CNN-LSTM performed well in identifying chickpea disease, with an accuracy of 92.55%.

Li *et. al.,* [11] presented a dual-optimization fault diagnosis method for rolling bearings based on white shark optimization hierarchical slope entropy (WSO-HSlopEn) and white shark optimization support vector machine (WSO-SVM). The white shark optimizer (WSO) is applied to optimize both HSlopEn and an SVM. The effectiveness of the proposed method was verified by comparing them with the classical methods. Experimental results on single- and multi-feature scenarios demonstrated that the WSO-HSlopEn and WSO-SVM fault diagnosis method has the highest recognition rate compared to other hierarchical entropies.

Fathy *et. al.,* [12] proposes a new efficient hybrid optimization approach for determining the proper parameters of Li-ion battery Shepherd model equivalent circuits. The proposed algorithm comprises a white shark optimizer (WSO) and the whale optimization approach (WOA) for modifying the stochastic behavior of the WSO while searching for food sources. The hybrid variant of the WSO (HWSO) was examined with two different types of batteries and the proposed HWSO was validated with a set of recent meta-heuristic approaches. The results prove the efficiency of the proposed approach in providing highly accurate battery model parameters with high consistency and a unique convergence curve compared to the other methods.

In Fathy and Alanazi [13], White Shark Optimizer (WSO) was used to evaluate the performance of proton exchange membrane fuel cell (PEMFC) design parameters that play a considerable role in boosting its effectiveness. The metaheuristic optimization mechanism WSO is employed to determine the parameters of the PEMFC equivalent circuit with the aid of experimental data recorded at certain temperature, pressure, and demand power conditions. The proposed WSO proved its effectiveness in establishing reliable equivalent circuits for different fuel cells at various operating conditions by attaining the best optimization results in terms of absolute error compared to the other considered algorithms.

The literature amass deep learning approaches for plant disease recognition and classification since it can automatically learn features from the input image. However, training the deep learning models with optimum feature subsets which guarantees reduced computational burden and better accuracy of recognition is germane and remains an open issue.

3. Methodology

The framework of this research is presented in Figure 3.1. The first stage is the acquisition of citrus fruit images, which was done by accessing a public repository of citrus data images online. The next is the pre-processing stage which involves filtering, cropping, normalization and conversion into grey scale to reduce noise and other irrelevant artefacts from the citrus images. White Shark Optimization was employed to select optimal CNN parameters such as weight parameters, number of layers, filter size and batch size from the extracted features and WSO-CNN was used to detect and classify infected citrus images from non-infected citrus images. The result of this procedure was evaluated using sensitivity, specificity, false positive rate and overall accuracy.

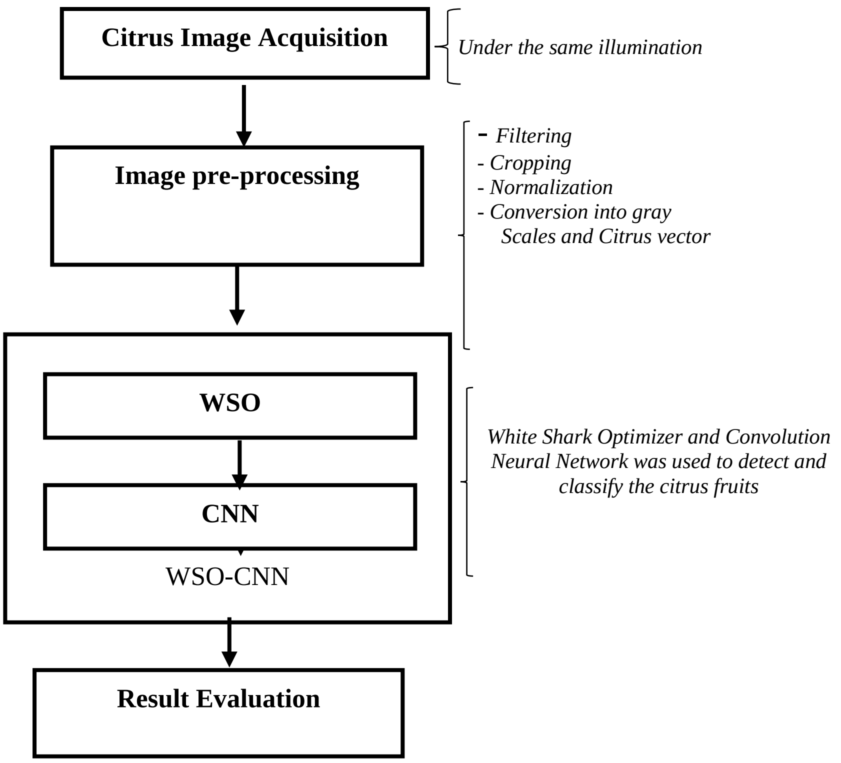

Figure 3.1: The process flow of the Citrus Disease Classification System

3.1 Acquisition of Citrus Images

Citrus images of 520 disease samples consisting of 210 sample of black spot, 120 samples of greasy spot and 190 samples of citrus canker and 520 of healthy and unhealthy samples were downloaded from an online public repository of citrus images (https://data.mendeley.com/datasets/3f83gxmv57/2. The original citrus images were resized into an arbitrary pixel sizes of 600 by 600 without any alteration in the images. A sample of each of the categories of the disease is shown in Figures 3.2 a, 3.2b, 3.3c and 3.4d for black spot, canker, greasy spot and healthy respectively.

Figure 3.2a: Sample of Black spot

Figure 3.2b: Sample of Canker

Figure 3.2c: Sample greasy spot

Figure 3.2d: healthy

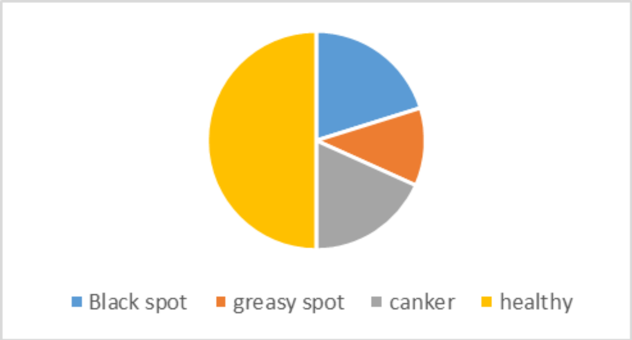

Figure 3.3: Dataset distribution

Figure 3.3 shows the distribution of the dataset. The figure shows that the distribution of the samples of healthy and unhealthy citrus is balance, hence model overfitting is prevented.

3.2 Image Pre-processing

Image pre-processing carried out in this research include image brightness and contrast alteration, filtering, cropping, grayscale conversion and normalization of the citrus image leaf vectors. This helps to remove noise and other unwanted element from the images. Each of the grayscale images was expressed and stored in form of matrix in MATLAB which was converted to vector image so as to further aid the normalization process.

Histogram equalization was used to improve the contrast in the images by stretching out the intensity range to enhance the brightness in the grayscale images for clearer view of the expression on each image. The normalization removes all common features that all the images shared and each image is left with its unique features. This was done by computing the average of all the image vectors and deducting this average from each image vector, resulting into a normalized image vector.

3.3 Feature Extraction and Classification using white shark-Convolution Neural Network (WSO-CNN)

The preprocessed images were passed on to CNN optimized by WSO. This optimization approach helps to efficiently improve the CNN. To achieve the best performance of the proposed approach, the hyper-parameters of the CNN which include number of layers, filters and batch size was optimized using WSO algorithm. After the convolutional and pooling layers, the fully connected layers are located to merge the features obtained and at the SoftMax layer the output is computed. The strategy was to combine fully connected layer blocks with a nonlinear mixture of the extracted features and also to execute the resultant classification.

3.3.1 The optimization of Hyper-parameter

The pre-trained CNN architectures have several limitations, notably is the need to readjust the hyperparameters which include batch size and unit size in every dense layer and the dropout layer. In this research, the WSO algorithm was employed in the CNN architecture models classifier section to optimize the batch size and dropout layer rate. The dynamic parameters optimized by WSO are the number of convolutional layers, the size of the filters used in each convolutional layer, the number of convolutional filters, and the batch size.

The general methodology of the proposed technique is presented in Figure 3.4 which expressed the flow of Convolutional Neural Network with White Shark Optimizer (WSO-CNN). The “training and optimization” block is the most important part of the whole process, where the CNN is initialized to integrate the parameter optimization by applying the WSO algorithm. In this process, the WSO is initialized according to the parameter given for the execution in Algorithm 3.1 and this generates the population. The training process is an iterative cycle that ends when all the white sharks generated by the WSO are evaluated for each generation. The computational cost is higher and, it depends on the database size, the size of white sharks, the number of iterations of the WSO and, the number of populations in each iteration. That is, if the WSO was executed with certain number of *population* and *iterations*, the CNN training process was executed *n* times. The steps to optimize the CNN by the WSO algorithm are illustrated in Figure 3.4 and explained as follows.

i. Input image database to train the CNN. This step consists of selecting the citrus leaves image database to be processed and classified for the CNN (recognize and non-recognize citrus).

ii. Generate the population for the WSO algorithm. The WSO parameters are set to include the number of iterations, the number of populations. This step involves the design of the white sharks.

iii. Initialize the CNN architecture, with the parameter obtained by the WSO (convolution layers number, the filter size, number of convolution filters, and the batch size) the CNN is initialized and in conjunction with the additional parameter specified, the CNN is ready to train the input citrus database.

iv. CNN training and validation: The CNN reads and processes the input citrus databases taking the images for training, validation, and testing; this step produces a recognition rate. These values return to the WSO as part of the objective function.

v. Evaluate the objective function: The WSO algorithm evaluates the objective function to determine the best value.

vi. Update WSO parameters. At each iteration, each population updates its velocity depending on its own best-known position (*pbest*) in the search-space and the best-known position globally (*gbest*).

vii. The process is repeated, evaluating all the white sharks until the stop criteria are found (in this case, it is the number of iterations).

viii. Finally, the optimal CNN parameters were selected. In this process, the WSO represented by *gbest* is the optimal one for the CNN model

3.3.2 Learning Phase

In the learning phase, the CNN architecture model was used to classify the citrus images. Hence, the feature extraction and parameter fine-tuning were achieved using VGG-19 transferring network model at this phase. There are 5 convolutional layers with their corresponding max pooling layer. The convolutional layer was fixed within the feature extraction process. There are several layers in the classifier: the fully connected layers consist of a dropout layer, flatten layer, batch normalization layer, and two dense layers.

The first fully connected layer consists of neuron groups with a rectified linear unit and the second fully connected layer consists of four function units of SoftMax. After training the classifier for the number of iterations the fine-tuning was achieved by reactivating the Convolutional last two layers and retraining with the classifier as shown in Figure 3.4. Once the training process is completed all these were merged to create the final prediction of Citrus image vectors which averages their posteriors of SoftMax class. The overall process of the citrus disease classification using Convolutional Neural Network with White Shark Optimizer (WSO-CNN) is shown in Figure 3.5

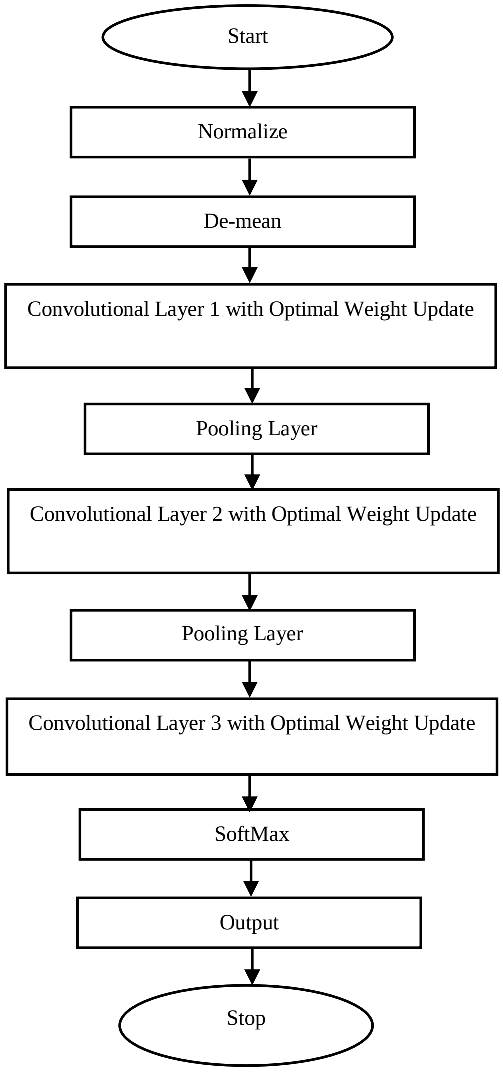

Figure 3.4: Process Flow of Convolutional Neural Network (CNN)

Algorithm 1: Pseudocode of the proposed White Shark Optimizer-Convolution Neural Network (WSO-CNN)

Step 1: Initialize CNN parameters such as no of layers, filter size, batch size, no of layers and weight.
Step 2: Initialize the parameters of WSO
Step 3: Randomly generate the initial positions of WSO
Step 4: Initialize the velocity of the initial population
Step 5: Evaluate the position of the initial population
Step 6: while (k<K) do

Update the parameters $\boldsymbol{v}$, $\boldsymbol{p_1}$, $\boldsymbol{p_2}$, μ, $\boldsymbol{a}$, b, $\boldsymbol{w_o}$, f, $\boldsymbol{m_v}$ and $\boldsymbol{s_s}$ using

$\boldsymbol{v} = [\mathbf{n}\,\mathbf{x}\,\boldsymbol{rand}(\mathbf{1},\boldsymbol{n})] + \mathbf{1}$ where $\boldsymbol{rand}(\mathbf{1},\boldsymbol{n})$ is a vector of random numbers generated with a uniform distribution in the range [0, 1].

$$\boldsymbol{p_1} = \boldsymbol{p_{max}} * (\boldsymbol{p_{max}} - \boldsymbol{p_{min}}) \times \boldsymbol{e}^{-(4k/K)^2}$$

$$\boldsymbol{p_2} = \boldsymbol{p_{min}} * (\boldsymbol{p_{max}} - \boldsymbol{p_{min}}) \times \boldsymbol{e}^{-(4k/K)^2}$$

Where $\boldsymbol{k}$ and $\boldsymbol{K}$ stand for the current and maximum number of iterations, respectively, $\boldsymbol{p_{min}}$ and $\boldsymbol{p_{max}}$ represent the initial and subordinate velocities to achieve good motion for white sharks.

$$\mu = \frac{\mathbf{2}}{\left|\mathbf{2} - \boldsymbol{\tau} - \sqrt{\boldsymbol{\tau}^2 - \mathbf{4}\boldsymbol{\tau}}\right|}$$

Where $\boldsymbol{\tau}$ denotes the acceleration coefficient which is equal to 4.125.

$$\boldsymbol{b} = \boldsymbol{sgn}(\boldsymbol{w}_k^i - \boldsymbol{l}) < \mathbf{0}$$

$$\boldsymbol{w_o} = \oplus\,(\boldsymbol{a}, \boldsymbol{b})$$

Where $\oplus$ is a bit-wise XOR operation.

$$\boldsymbol{f} = \boldsymbol{f_{min}} + \frac{\boldsymbol{f_{max}} - \boldsymbol{f_{min}}}{\boldsymbol{f_{max}} + \boldsymbol{f_{min}}}$$

Where $\boldsymbol{f_{max}}$ and $\boldsymbol{f_{max}}$ denote the minimum and maximum frequencies of the undulating motion, respectively, and rand represents a random number uniformly dispensed within the scope [0, 1].

$$\boldsymbol{m_v} = \frac{\mathbf{1}}{(\boldsymbol{a_o} + \boldsymbol{e}^{(k/2)-k)/a_1})}$$

Where $\boldsymbol{a_o}$ and $\boldsymbol{a_1}$ are two positive constants employed to manage exploration and exploitation behaviors. $\boldsymbol{m_v}$ express the strength of the white shark's sense of hearing and smell, which increases as a function of iterations.

$$\boldsymbol{s_s} = |\mathbf{1} - \boldsymbol{e}^{(-a_2 \times \frac{k}{K})}|$$

Where $\boldsymbol{a_2}$ is a positive constant utilized to control exploration and exploitation behaviors.

Step 7: For j=1 to n do

$$\boldsymbol{v_{t+1}}^j = \mu[\boldsymbol{v_k}^i + \boldsymbol{p_1}\,([\boldsymbol{w_{gbest_k}} - \boldsymbol{w_k}^i] \times \boldsymbol{c_1} + \boldsymbol{p_2}([\boldsymbol{w_{best}}^{\boldsymbol{v_k}^i} - \boldsymbol{w_k}^i] \times \boldsymbol{c_2}]$$

End for

Step 8: For i=1 to n do

if *rand* < $\boldsymbol{m_v}$ then

$$\boldsymbol{w}_{k+1}^i = \boldsymbol{w}_k^i . \neg \oplus \boldsymbol{w_o} + \boldsymbol{u}.\boldsymbol{a} + \boldsymbol{l}.\boldsymbol{b}$$

Else

$$\boldsymbol{w}_{k+1}^i = \boldsymbol{w}_k^i + \boldsymbol{v}_k^i / \boldsymbol{f}$$

End if

End for

Step 9: For i=1 to n do

if *rand* < $\boldsymbol{s_v}$ then

$$\overrightarrow{\boldsymbol{D_w}} = |\boldsymbol{rand} \times (\boldsymbol{w_{gbest_k}} - \boldsymbol{w}_k^i)|$$

If i==1 then

$$\boldsymbol{w}_{k+1}^i = \boldsymbol{w_{gbest_k}} + \boldsymbol{r_1}\overrightarrow{\boldsymbol{D_w}}\boldsymbol{sgn}(\boldsymbol{r_2} - \mathbf{0.5})$$

Else

$$\boldsymbol{w}_{k+1}^i = \boldsymbol{w_{gbest_k}} + \boldsymbol{r_1}\overrightarrow{\boldsymbol{D_w}}\boldsymbol{sgn}(\boldsymbol{r_2} - \mathbf{0.5})$$

$$\boldsymbol{w}_{k+1}^i = \frac{\boldsymbol{w}_k^i - \boldsymbol{w}_{k+1}^i}{2 \times \boldsymbol{rand}}$$

End if
End if
End for

Adjust the position of the white sharks that proceed beyond the boundary
Evaluate and update the new positions

$\boldsymbol{k} = \boldsymbol{k} + \mathbf{1}$

End while

Step 10: Output optimal no of layers, filter size, batch size, weight

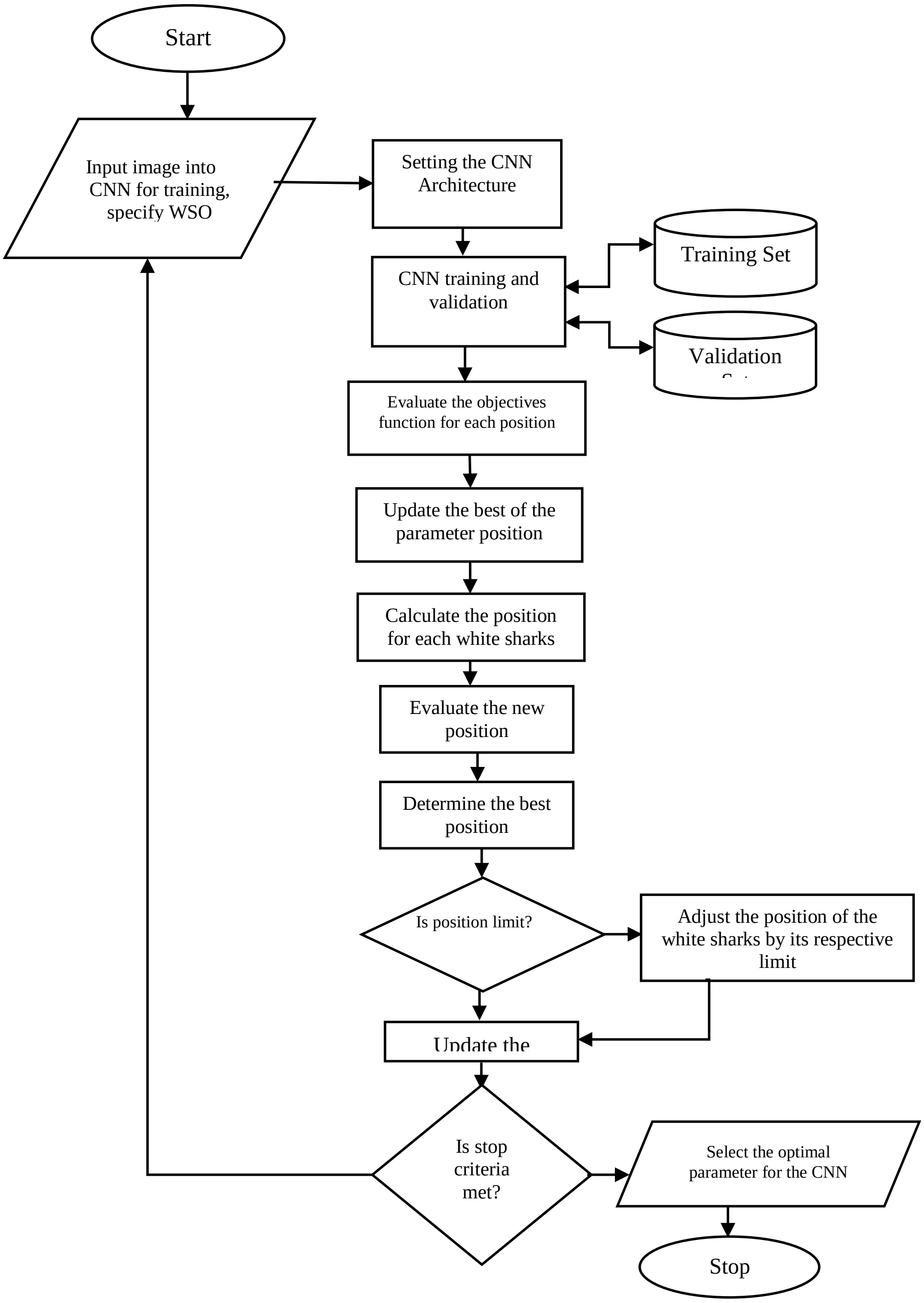

Figure 3.5: Process Flow of (WSO-CNN)

3.4. Performance Evaluation Metrics

The performance of the WSO-CNN on both trained and recognized citrus diseases were evaluated based on recognition accuracy, false positive rate, sensitivity, specificity and average recognition time. Confusion matrix was used to determine the value of the performance metrics. It contains “True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN). TP contains amount of entries for the tuple that correctly identified as positive. FP contains the amount of entries for the tuples which are negative but predicted as positive. TN is the amount of tuples that are negative and predicted as negative. FN is the amount of tuples that are positive but predicted as negative. Also, Precision, recall, specificity and accuracy was calculated using these terms.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad 3.1$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad 3.2$$

$$\text{False Positive Rate} = \frac{\text{FP}}{\text{TN} + \text{FP}} = 1 - Specificity \quad 3.3$$

$$\text{Overall Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad 3.4$$

$$\text{Average recognition time} = \frac{\text{Total Recognition Time}}{\text{Number of recognized citrus disease}} \quad 3.5$$

4. Results of Experiments

The evaluation results of performance of the proposed technique are based on the aforementioned categories of citrus diseases: black spot (BS), greasy spot (GS) and Canker (CCK) dataset. The WSO-CNN and CNN were used as the classifier for the extraction technique. The optimum performance was achieved at learning rate value of 0.75 for all technique with respect to the experimented datasets.

4.1 Evaluation of Results Using the Black Spot (BS) Dataset

Table 4.1 presents the results obtained by the CNN and WSO-CNN technique with respect to the performance metrics using Black spot datasets. The table reveals that CNN technique achieved a false positive rate of 8.33%, sensitivity of 90.48%, specificity of 91.67%, and accuracy of 90.95% at 96.43seconds. Similarly, the WSO-CNN technique achieved a false positive rate of 4.76%, sensitivity of 99.21%, specificity of 95.24%, and accuracy of 97.62% at 74.94 seconds. The result obtainable from Table 4.1 reveals that the WSO-CNN technique outperformed CNN technique in terms of false positive rate, sensitivity, specificity and recognition accuracy.

4.2 Evaluation of Results Using the Greasy Spot (GS) Dataset

Table 4.2 presents the results obtained by the CNN and WSO-CNN technique with respect to the performance metrics using Greasy spot datasets. The table reveals that CNN technique achieved a false positive rate of 10.42%, sensitivity of 90.28%, specificity of 89.58%, and accuracy of 90.00% at 50.65 seconds. Also, the WSO-CNN technique achieved a false positive rate of 2.08%, sensitivity of 98.61%, specificity of 97.92%, and accuracy of 98.33% at 49.52 seconds. The result obtainable from Table 4.2 reveals that the WSO-CNN technique outperformed CNN technique in terms of false positive rate, sensitivity, specificity and recognition accuracy.

Table 4.1: Results obtained by the CNN and WSO-CNN technique with Black spot (BS), datasets.

Technique	Sensitivity (%)	Specificity (%)	FPR (%)	Accuracy (%)	Recognition Time (seconds)
CNN	90.48	91.67	8.33	90.95	96.43
WSO-CNN	99.21	95.24	4.76	97.62	74.94

Table 4.2: Results obtained by the CNN and WSO-CNN technique with Greasy spot (GS) datasets.

Technique	Sensitivity (%)	Specificity (%)	FPR (%)	Accuracy (%)	Recognition Time (seconds)
CNN	90.28	89.58	10.42	90.00	50.65
WSO-CNN	98.61	97.92	2.08	98.33	49.52

Table 4.3: Results obtained by the CNN and WSO-CNN technique with Canker (CCK) datasets.

Technique	Sensitivity (%)	Specificity (%)	FPR (%)	Accuracy (%)	Recognition Time (seconds)
CNN	87.72	93.42	6.58	90.00	84.31
WSO-CNN	98.25	97.37	2.63	97.89	72.27

4.3 Evaluation of Results using the Canker (CCK) dataset

Table 4.3 presents the results obtained by the CNN and WSO-CNN technique with respect to the performance metrics using Canker datasets. The table reveals that CNN technique achieved a false positive rate of 6.58%, sensitivity of 87.72%, specificity of 93.42%, and accuracy of 90.00% at 84.31 seconds. Similarly, the WSO-CNN technique achieved a false positive rate of 2.63%, sensitivity of 98.25%, specificity of 97.37%, and accuracy of 97.89% at 72.27 seconds. The result obtainable from Table 4.3 reveals that the WSO-CNN technique outperformed CNN technique in terms of false positive rate, sensitivity, specificity and recognition accuracy.

4.4 Evaluation of Results using the Healthy and Non-Healthy dataset

Table 4.4 presents the results obtained by the CNN and WSO-CNN technique with respect to the performance metrics using Healthy and Non-Healthy datasets. The table reveals that CNN technique achieved a false positive rate of 14.00%, sensitivity of 95.48%, specificity of 86.00%, and accuracy of 93.65% at 179.43 seconds. Similarly, the WSO-CNN technique achieved a false positive rate of 5.00%, sensitivity of 99.29%, specificity of 95.00%, and accuracy of 98.46% at 167.94 seconds. The result obtainable from Table 4.4 reveals that the WSO-CNN technique outperformed CNN technique in terms of false positive rate, sensitivity, specificity and recognition accuracy.

4.5 Performance Evaluation of combined result for All Tested Dataset

The experimental results discussion in terms of total recognition time, accuracy, FPR, sensitivity and specificity of the citrus disease detection and classification system are presented in this section. Table 4.5 depicts the combined results for WSO-CNN and CNN with respect to the datasets used. It can be inferred from the results presented in Table 4.5 that the WSO-CNN technique gave an increased 6.67%, 8.33%, 7.89% and 4.81% recognition accuracy for black spot, greasy spot, canker and healthy/non healthy dataset respectively over the CNN technique.

The improved recognition accuracy is due to the fact that the features of CNN optimized by WSO results into a more discriminating features which yield an increased performance. Also, WSO-CNN technique gave an increased 3.57%, 8.34%, 3.95% and 9.00% specificity for black spot, greasy spot, canker and healthy/non healthy dataset respectively over the CNN technique. Furthermore, WSO-CNN technique gave an increased 8.73%, 8.33%, 10.53% and 3.81% sensitivity for black spot, greasy spot, canker and healthy/non healthy dataset respectively over the CNN technique.

Table 4.4: Results obtained by the CNN and WSO-CNN technique with Healthy and Non Healthy datasets.

Technique	Sensitivity (%)	Specificity (%)	FPR (%)	Accuracy (%)	Recognition Time (seconds)
CNN	95.48	86.00	14.00	93.65	179.43
WSO-CNN	99.29	95.00	5.00	98.46	167.94

Table 4.5: Combined results for WSO-CNN and CNN with respect to the datasets

	Black spot	**Greasy spot**	**Canker**	**Healthy/Non Healthy**
Accuracy (%)				
CNN	90.95	90.00	90.00	93.65
WSO-CNN	97.62	98.33	97.89	98.46
Sensitivity (%)				
CNN	90.48	90.28	87.72	95.48
WSO-CNN	99.21	98.61	98.25	99.29
Specificity (%)				
CNN	91.67	89.58	93.42	86.00
WSO-CNN	95.24	97.92	97.37	95.00
Recognition time (%)				
CNN	96.43	50.65	84.31	179.43
WSO-CNN	74.94	49.52	72.27	167.94
FPR (%)				
CNN	8.33	10.42	6.58	14.00
WSO-CNN	4.76	2.08	2.63	5.00

The recognition accuracy, specificity, sensitivity, recognition time and FPR of the citrus disease detection and classification system achieved by the techniques evaluated in this study reveals the WSO-CNN technique achieved an increase performance as shown in Figures 4.1, 4.2a, 4.2b and 4.2c and 4.2d for all category of dataset used in this study.

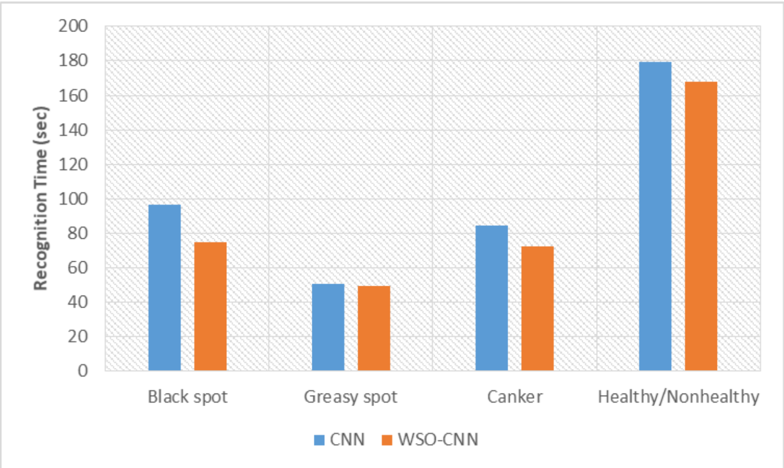

Figure 4.1: Comparison of Total Recognition time for Citrus disease detection and classification system

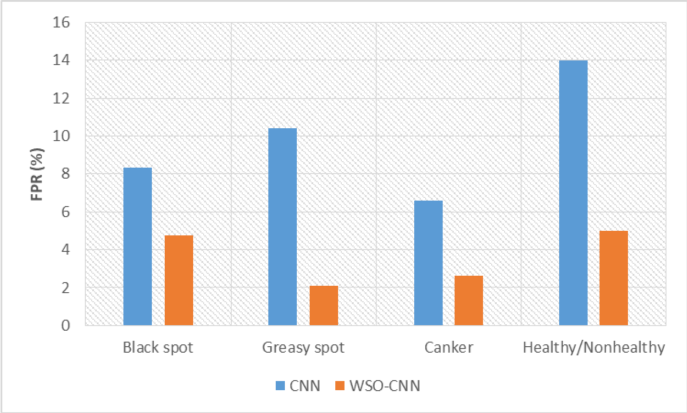

Figure 4.2a: Comparison of FPR for Citrus disease detection and classification system

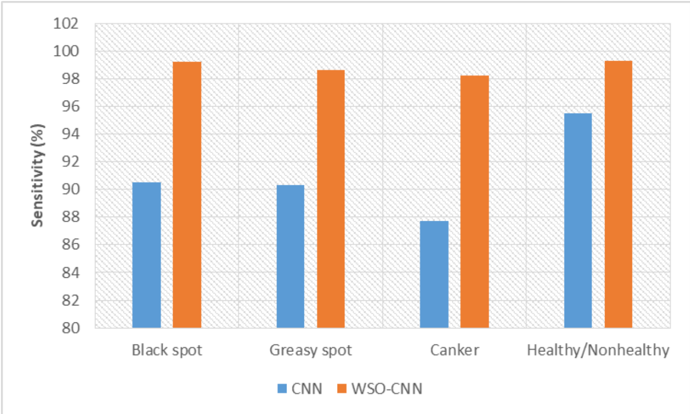

Figure 4.2b: Comparison of Sensitivity for Citrus disease detection and classification system

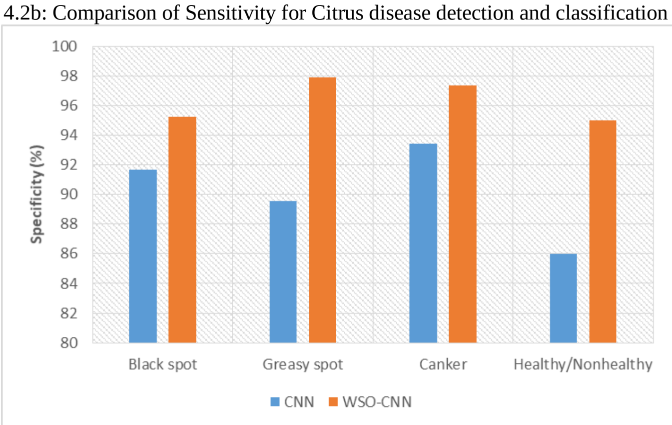

Figure 4.2c: Comparison of Specificity for Citrus disease detection and classification system

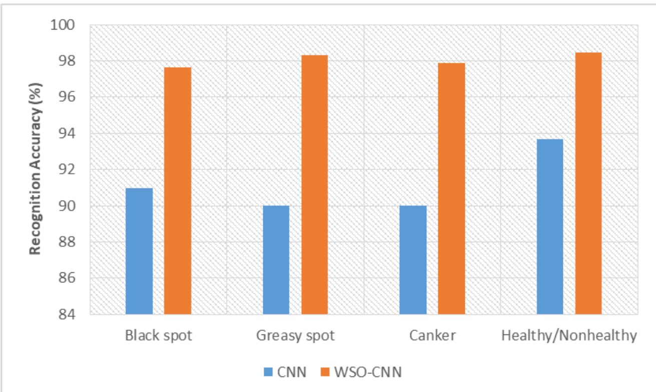

Figure 4.2d: Comparison of Recognition Accuracy for Citrus disease detection and classification system

The improved performance in terms of sensitivity, specificity and FPR achieved the WSO-CNN technique over CNN is attributed to the adaptive learning rate of the WSO-CNN. This also corroborated the work of Nisha [14] and Khaire & Dhanalakshmi [15] who both observed that a feature selection could increase the recognition accuracy rate. Nisha [14] observed that features optimized by employing WSO algorithm consequently improved classification accuracy. Khaire and Dhanalakshmi [15] used feature selection and achieved a very high discriminating features with high classification rates.

In view of the above result, the combination of CNN and WSO technique results to an improved accuracy, specificity, sensitivity and FPR for all dataset used in the study. This implies that the WSO-CNN technique was able to achieve more quality solution than the existing CNN techniques. Hence, WSO-CNN technique outperformed CNN technique in terms of the aforementioned metrics with respect to the detection and classification of the citrus diseases, that is, WSO-CNN technique is more sensitive, specific, and accurate. Furthermore, the false positive rate achieved by the WSO-CNN technique further proves its correctness.

This research has contributed to the body of knowledge by developing a White Shark Optimizer – Convolution Neural Network as feature selection and classification technique for detecting and classifying citrus fruit diseases which has a faster learning process, and high accuracy rate. The technique was able to classify healthy and unhealthy fruits which has greatly improved detection of infected citrus fruits which can prompt early treatment and elimination of affected ones.

5. Conclusion and Further work

This research implemented an optimization technique for citrus disease detection and classification system. One thousand and forty (1040) images comprising four categories of datasets namely black spot (BS), greasy spot (GS), Canker (CCK) and healthy/non healthy were used in the evaluation of the developed technique. These images were trained and tested with the developed (WSO-CNN) at different learning rate value. In all the evaluations conducted, the developed WSO-CNN technique achieved an improved recognition accuracy, false positive rate, sensitivity, computational time and specificity.

With regard to the performance of the developed technique; the WSO-CNN technique can be used to handle challenges associated with citrus disease detection and classification system in the prevention of related citrus disease. In view of the results obtained, the performance of deep learning techniques can be improved upon using optimization and evolutionary search algorithms.

Competing Interest

The Authors declare that there is no competing interest in the experimental procedure and preparation of the manuscripts

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