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Development of a Coati-Optimised Convolutional Neural Network for infected citrus fruit detection and classification system

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ABSTRACT

Pest and disease management plays a significant role in minimizing losses to crops, particularly in citrus fruit production. Traditional methods for detecting and classifying infected citrus fruits are complex and tasking, while Convolutional Neural Networks (CNNs) offer promising solutions but still face challenges such as high computational requirements and data dependency. Therefore, this study developed an improved convolution neural network for infected citrus fruit detection and classification system using Coati Optimisation Algorithm (COA). A dataset of 1,790 citrus images, containing samples of black spot, greening spot, citrus canker, and healthy fruits, was acquired from www.kaggle.com. The images underwent preprocessing involving cropping to remove unwanted elements, conversion to grayscale to simplify processing, normalization to enhance data consistency and reduce redundancy, and filtering to minimize noise. An optimised CNN model was formulated using COA to tune the hyperparameters (weight and learning rate) of CNN to produce Coati Optimisation Algorithm–based Convolutional Neural Network (COA-CNN). The preprocessed images serve as input to the COA-CNN model. The COA-CNN was used for the extraction of edges, corners, texture, patterns and shapes, and classification of citrus fruits as infected or healthy. The developed system was implemented using MATLAB R(2023a). The system's performance was evaluated using accuracy, false positive rate, sensitivity, specificity, and recognition time. A comparative analysis of CNN and COA-CNN was also carried out. The accuracy, false positive rate, sensitivity, specificity, and recognition time for CNN were 95.83%, 6.02%, 96.63%, 93.98% and 202.17 s, respectively, while the corresponding values for COA-CNN were 96.92%, 4.22%, 97.41%, 95.78% and 136.86 s. This research showed that COA-CNN performed better and is recommended for citrus disease detection and classification systems.

INTRODUCTION

Controlling pests and diseases is now an important step in lowering crop losses (Ola *et al.,* 2020). The Mediterranean Fruit Fly (MFF) is one of the most devastating pests that harms agricultural goods like citrus fruits (Mahfouz, 2021). This pest has been able to spread quickly around the globe due to its fast rate of reproduction, adaptability to various climatic conditions, and absence of natural adversaries, considering the existence of over 350 species of hosts (fruits and vegetables) for it (Díaz and Regil, 2013). The female fly bites the fruit and deposits eggs inside it. The eggs hatch into larva that feed on the fruit, which causes gradual spoilage as a result of fungi and bacteria getting inside the fruit through the tunnelling created by the larva's feeding. The larva then leaves the fruit to pupate and falls to the ground (Hadipour-Rokni *et al.*, 2023).

Citrus peels with infections or other flaws often sell for less money, and in certain places, they may even be impossible to import or export. Citrus Canker and

Citrus Black Spot (CBS) fall into the latter group, whereas other less serious peel issues, including melanose, greasy spot, wind damage, and insect damage, may simply have an impact on fruit prices. The devastating disease citrus canker, which has plagued Florida's citrus industry for over 20 years, causes visible, eruptive lesions on fruit, leaves, and stems. Defoliation, fruit blemishes, premature fruit drop, twig dieback, and overall tree decline are among its impacts (Gottwald *et al*., 2002).

Canker is regarded as one of the deadliest diseases that endangers fresh market citrus harvests. At best, canker decreases consumer attractiveness, and at worst, canker prevents whole shipments of fruit from being exported (Dewdney *et al*., 2021). To reduce losses from canker, diseased citrus must be found and removed at or before the packinghouse, but doing so manually is time and money-consuming. To ensure fruit quality and safety as well as increase the competitiveness and profitability of the citrus industry, automated identification of citrus peel conditions that not only detects more serious infections but also distinguishes between them and superficial blemishes is needed (Yadav *et al*., 2022). Identification and classification of citrus diseases are crucial steps in achieving the highest economic value of citrus.

Citrus disease classification, the key step in citrus disease processing, is increasingly carried out by machine learning rather than manually using tools like pattern recognition and computer image processing (Ogundepo *et al.,* 2022; Chen *et al*., 2023). In addition to resolving issues with human sorting, including low productivity and inconsistent classification standards, automated fruit categorisation by machine vision may enhance classification precision (Kondo and Ting, 2018). To categorise plant diseases, many conventional machine learning (ML) techniques have been used. While there are different advanced architectures, including AlexNet, the Visual Geometry Group (VGG), DenseNet, Inception-v4, and ResNet have shown promising results for the classification of plant diseases since the development of deep learning (DL) (Saleem *et al*., 2020). This is because Deep Learning (DL) algorithms can automatically extract feature information (Okediran and Oguntoye, 2023).

Deep learning is currently often used in a broad range of fields, including segmentation (Gour *et al*., 2019; Oguntoye *et al,* 2023), object identification, voice and signal recognition, biomedical image classification, and signal and speech recognition (Gour and Jain, 2020). The application of deep learning techniques in plant disease classification is a remarkable development in agricultural sciences. Saleem *et al*. (2020) state that the Convolutional Neural Network (CNN) is considered the most powerful deep learning method, having been extensively used in digital image processing. Various CNN architectures, including AlexNet and GoogLeNet, are utilised for plant disease detection and classification (Atanda *et al,* 2023). Besides, many studies have specifically concentrated on applying deep learning models for citrus disease identification and classification, as discussed by Barman and Ridip (2022). Various studies have thus developed methods targeted at improving the diagnostic accuracy of plant diseases by using CNNs with various optimisation algorithms.

The Coati Optimisation Algorithm (COA) is an emerging computational method inspired by the natural foraging behaviour of coatis, which are social animals known for their cooperative hunting tactics. Researchers developed COA by observing how coatis utilise group collaboration and individual exploration to search for food, mimicking this process to solve optimisation problems. Optimisation algorithms are widely used in fields such as engineering, artificial intelligence, and operational research, where the goal is to find the best solution from a set of possible alternatives. Unlike traditional algorithms, COA leverages the social dynamics of coati behaviour to balance exploration and exploitation, which can improve solution accuracy and computational efficiency (Ola *et al.,* 2019; Ola *et al.,* 2020). The development of COA provides a novel and biologically-inspired approach to addressing complex optimisation problems, with potential applications in various optimisation tasks across diverse domains. Hence, a Coati Optimisation Algorithm-based Convolution Neural Network (COA-CNN) was developed to extract features, detect and classify infected citrus fruit diseases.

METHODOLOGY

Research Approach

The dataset of citrus images downloaded from the internet was used, and it was preprocessed by converting the citrus images into a grey scale to reduce computational complexity and normalisation of citrus images to reduce noise. A CNN model, trained using the hyperparameters optimised by the COA, was used for feature extraction and classification of non-infected and infected citrus samples. The classification results were then evaluated.

Acquisition of Citrus Images

Citrus images of 1790 disease samples, consisting of some samples of black spot, greening spot, citrus canker and a healthy dataset was downloaded from the online dataset www.kaggle.com. Data augmentation, such as flipping and rotation, was performed on the dataset. The original citrus images were resized to an appropriate pixel size of 600 by 600, without compromising the integrity of the images. All images were trained and tested using the k-fold method, where k is 10-fold.

Image Preprocessing

Image pre-processing refers to processes like adjustment of image brightness, contrast, scaling, filtering, cropping, and other techniques used to improve images. In this work, the images obtained from the digital camera are three-dimensional (3-D) colour images that must be converted into two-dimensional (2-D) grayscale images with pixel values ranging from 0 to 255, essentially black and white images. Each grayscale image is expressed as a matrix and was initially stored in MATLAB before being converted into a vector format, referred to as the citrus image vector. This conversion aids in the subsequent normalisation process.

Normalisation was obtained through the use of a histogram equalisation algorithm on the grayscale images, allowing for the contrast enhancement with an amplified intensity range. This increased the brightness greatly, thus providing better distinguishable features of the citrus. During this process, common features shared across all citrus images were eliminated to ensure that each image retains unique characteristics. These common features were identified by computing the average citrus vector across the training dataset, which was then subtracted from each citrus vector to produce a normalised citrus vector.

Development of Coati Optimisation Algorithm based Convolutional Neural Network

A CNN model's key hyperparameters, like weights and learning rate, were optimised by COA, which represents candidate solutions as agents randomly placed in the search space. COA evaluates each agent's fitness based on CNN performance, simulating coati behaviors to balance exploration and exploitation, iteratively updating agents to find optimal values. After convergence, the optimised hyperparameters are used to train the convolutional neural network on the whole dataset for improved performance.

Design of an Optimised CNN for Infected Citrus Fruits Detection and Classification System

The CNN model was trained using the hyperparameters selected by COA, involving forward and backwards propagation and weight adjustment based on the optimiser's algorithm. The model's performance was evaluated on a validation dataset using metrics like accuracy or MSE. The final CNN was trained with the optimal hyperparameters on the full training dataset and tested on a separate test dataset. During training, the optimiser uses a probabilistic model of hyperparameter behaviour to efficiently explore the search space, outperforming grid or random search methods. Figure 1 shows the flowchart of training and testing citrus with COA-CNN.

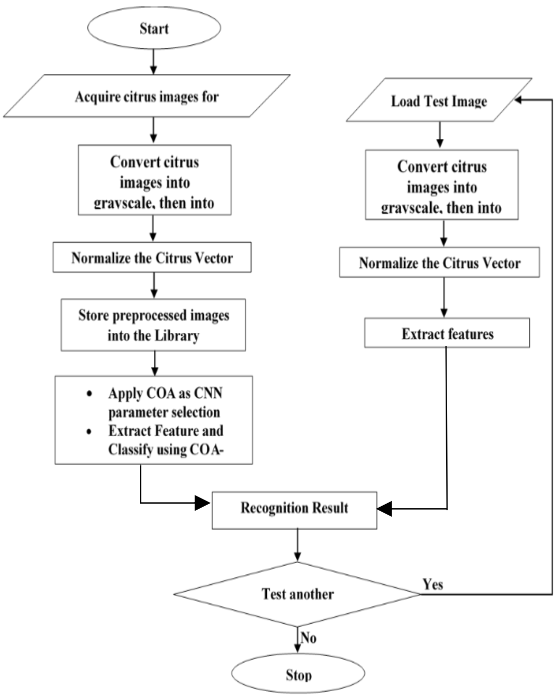

Figure 1: Flowchart showing trained and tested citrus with COA-CNN

Implementation

An interactive Graphical User Interface (GUI) application was developed with an online database of citrus fruit disease dataset showing the training and testing process of CNN and COA-CNN techniques. The graphical user interface (GUI) was created using the image processing toolbox and deep learning, and optimisation toolboxes in MATLAB (2023a). All implementations were done using the MATLAB software package on a computer with the specific configuration.

Performance Evaluation

The metrics used were accuracy, sensitivity, specificity, false positive rate, and recognition time for the performance of the developed technique.

Accuracy: is defined as the ability of a classification model to detect all datasets in citrus fruit, and is given by:

$$Accuracy(\%) = \frac{TP + TN}{TP + FP + TN + FN} * 100 \qquad (3.1)$$

Specificity is defined as the ability of a classification model to detect healthy citrus fruit, and is given by:

$$Specificity(\%) = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} * 100 \qquad (3.2)$$

Sensitivity is defined as the ability of a classification model to detect unhealthy citrus fruit, and is given by:

$$Sensitivity(\%) = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} * 100 \qquad (3.3)$$

False Positive Rate is defined as the rate at which the classification model incorrectly predicts a healthy citrus fruit as unhealthy.

$$\text{False Positive Rate } (\%) = \frac{\mathrm{FP}}{\mathrm{FP} + TN} * 100 \qquad (3.4)$$

Recognition Time is the time taken by the system to recognise an image. The performance of the method was assessed using the citrus disease: black spot (BS), greening (GS) and Canker (CCK) datasets.

RESULTS AND DISCUSSION

The results of the implementation of the Coati Optimisation Algorithm, used to extract features and classify infected citrus fruits, are presented in this section. The training and testing phases of the CNN and COA-CNN methods were illustrated in

Figures 2 and 3. The results of the aforementioned method are based on the following categories of citrus diseases, which are: black spot (BS), greening (GS), and Canker (CCK) datasets. For the extraction technique, the COA-CNN and CNN classifiers were used. The performance of the technique was affected by the threshold value. The best performance in relation to the above datasets was obtained using a threshold value of 0.80 for all techniques.

Evaluation of results using the black spot (BS) dataset

Table 1 illustrate the outcome obtained from the implementation of the CNN and COA-CNN method with the provided performance metrics using the Blackspot datasets. It indicates that, for the CNN technique, the result for the False positive rate was found to be 7.77%, Sensitivity 95.44%, Specificity 92.23%, and accuracy 94.48% at 64.35 seconds. On the other hand, the COA-CNN approach recorded 3.88% for false positive rates, 97.10% for sensitivity, 96.12% for specificity, and 96.80% for accuracy at 42.97 seconds. The result provided in Table 1 allows to state that in terms of COA-CNN, there is better performance than in the case of CNN regarding all the parameters: false positive rate, sensitivity, specificity, accuracy, and recognition time.

Table 1: Results obtained by the CNN and COA-CNN technique with Blackspot (BS) datasets

Technique	FPR (%)	Specificity (%)	Sensitivity (%)	Accuracy (%)	Recognition Time (secs)
CNN	7.77	92.23	95.44	94.48	64.35
COA-CNN	3.88	96.12	97.10	96.80	42.97

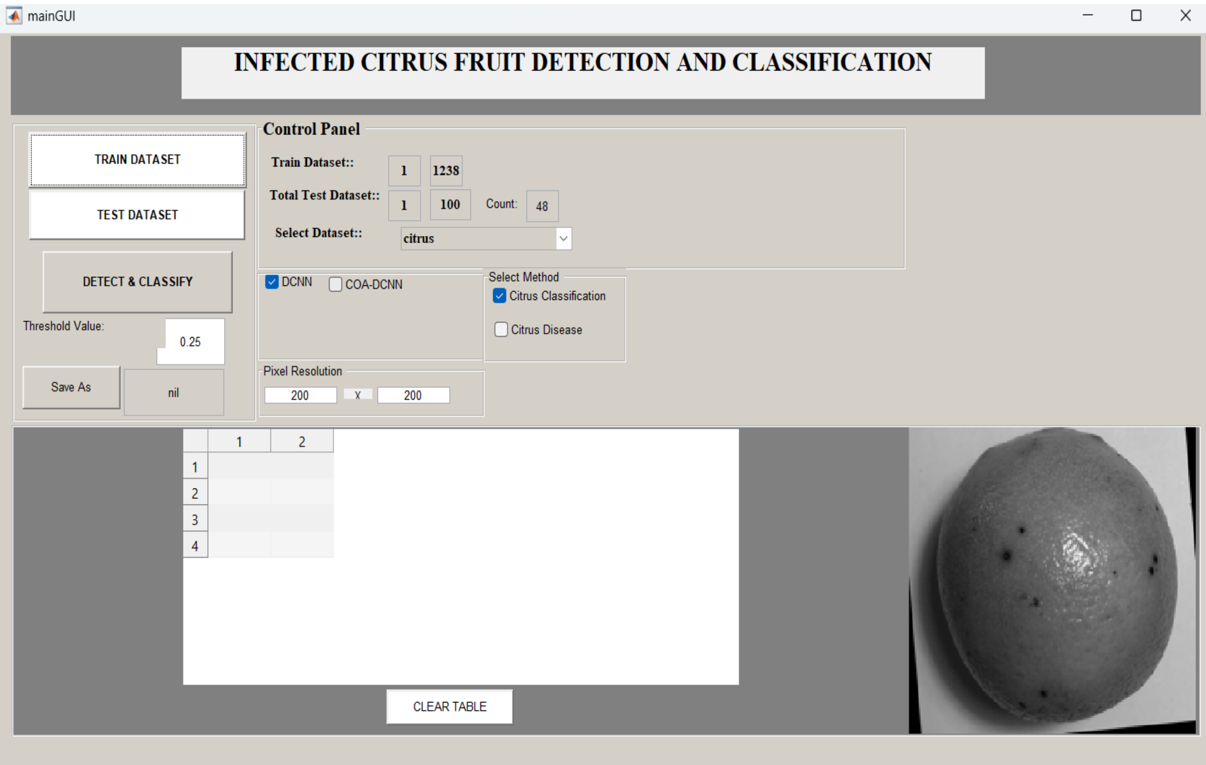

Figure 2: GUI showing the Training Process

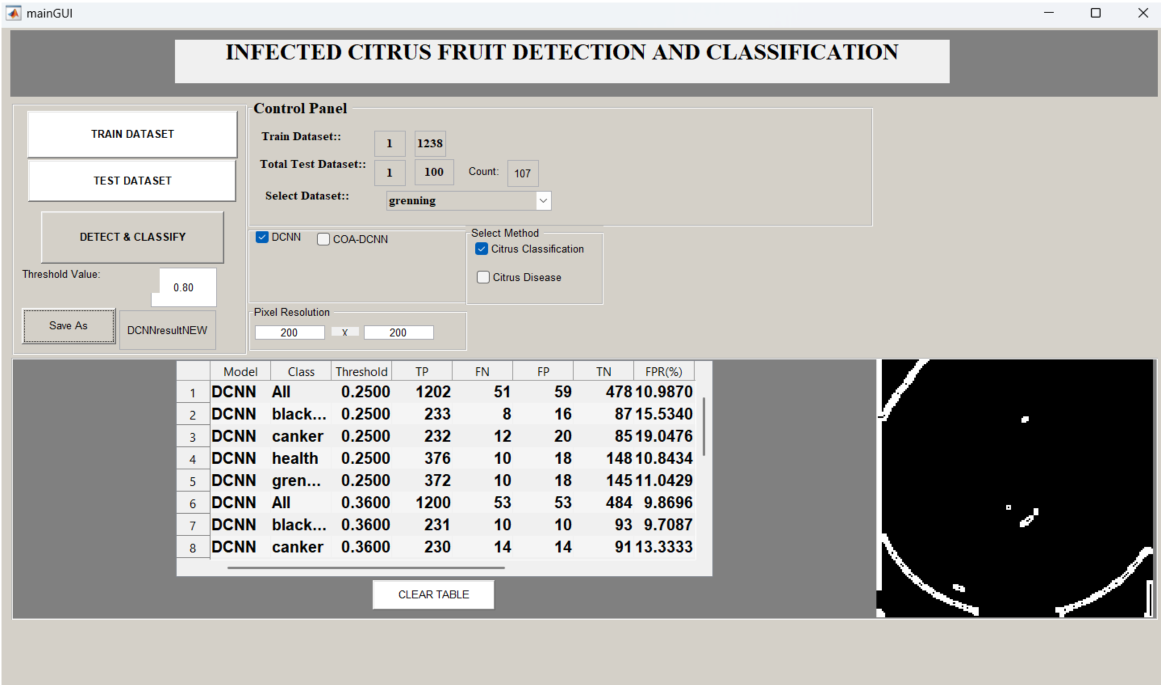

Figure 3: GUI showing the Testing Process

Table 2: Results obtained by the CNN and COA-CNN technique with Greening (GS) datasets.

Techniques	**FPR (%)**	**Specificity (%)**	**Sensitivity (%)**	**Accuracy (%)**	**Recognition Time (secs)**
CNN	6.13	93.87	96.60	95.78	64.94
COA-CNN	4.29	95.71	97.38	96.88	43.02

Evaluation of Results using the Greening (GS) dataset

The results from CNN and COA-CNN techniques with respect to the performance metrics using Greening datasets are detailed in Table 2. According to the findings, the CNN technique obtained a false positive rate of 6.13%, sensitivity of 96.60%, specificity of 93.87%, and accuracy of 95.78% at a time of 64.94 seconds. Furthermore, the COA-CNN technique obtained a false positive rate of 4.29%, sensitivity of 97.38%, specificity of 95.71%, and accuracy of 96.88% at a time of 43.02 seconds. The data provided in Table 2 indicates that the COA-CNN technique surpassed the CNN technique regarding false positive rate, sensitivity, specificity, accuracy, and recognition time.

Evaluation of Results using the Canker (CCK) dataset

According to the performance metrics results derived from the COA-CNN and CNN techniques, as represented in Table 3, datasets on canker demonstrate a 11.43% false positive rate, 93.85% sensitivity, 88.57% specificity, and 92.26% accuracy for CNN technique, which utilized 65.04 seconds. In the same table, COA-CNN reported 4.76% false positives, 96.72% sensitivity, 95.24% specificity, and 96.28% accuracy, which was recorded at 42.99 seconds. The output analysis from Table 3 suggests that COA-CNN has a lower negative rate, higher sensitivity, greater specificity, higher accuracy, and quicker recognition time,

Table 3: Results obtained by the CNN and COA-CNN technique with Canker (CCK) datasets

	Blackspot	Greening	Canker	Healthy
Accuracy (%)				
CNN	94.48	95.78	92.26	95.83
COA-CNN	96.80	96.88	96.28	96.92
Sensitivity (%)				
CNN	95.44	96.60	93.85	96.63
COA-CNN	97.10	97.38	96.72	97.41
Specificity (%)				
CNN	92.23	93.87	88.57	93.98
COA-CNN	96.12	95.71	95.24	95.78
Recognition time (sec)				
CNN	64.35	64.94	65.04	191.36
COA-CNN	42.97	43.02	42.99	124.54
False Positive Rate (%)				
CNN	7.77	6.13	11.43	6.02
COA-CNN	3.88	4.29	4.76	4.22

Table 4: Results obtained by the CNN and COA-CNN techniques with healthy datasets

Technique	**FPR (%)**	**Specificity (%)**	**Sensitivity (%)**	**Accuracy (%)**	**Recognition Time (secs)**
CNN	11.43	88.57	93.85	92.26	65.04
COA-CNN	4.76	95.24	96.72	96.28	42.99

proving the performance advantage over the CNN technique.

.**Evaluation of Results using the Healthy dataset**

Table 4 shows the performance of the CNN and COA-CNN approaches compared with different performance measures when tested with Healthy datasets. The results show that the CNN approach yielded a false positive rate of 6.02%, a sensitivity of 96.63%, a specificity of 93.98%, and an accuracy of 95.83%, with a recognition time of 191.36 seconds. The COA-CNN approach achieved a false positive rate of 4.22%, a sensitivity of 97.41%, a specificity of 95.78%, and an accuracy of 96.92%, with a recognition time of 124.54 seconds. The results shown in Table 4 reveal that the COA-CNN approach outperformed the CNN approach with respect to false positive rate, sensitivity, specificity, accuracy, and recognition time.

Discussion of Results

This section presents a discussion of the experimental results relative to the recognition time, accuracy, FPR, specificity and sensitivity of the citrus disease detection and classification system. Figures obtained by the COA-CNN and the CNN are presented in the form of Table 5 based on the datasets used. Recognition time, accuracy, specificity, FPR and sensitivity of the citrus disease detection and classification system derived with the methods used in this study ascertain the COA-CNN method as the one having the best performance for all the types of datasets used in this study.

The results in Table 5 indicate that the COA-CNN method provided a higher 2.32%, 1.10%, 4.02% and 1.09% accuracy for the dataset of black spot, greening, canker and healthy, respectively, over the CNN method because the CNN's parameter optimised by COA leading towards a discriminative parameter yielding a better performance. The COA-CNN method also provided a higher 3.89%, 1.84%, 6.67% and 1.80% specificity for the dataset of black spot, greening, canker and healthy, respectively, over the CNN method. COA-CNN method provided a higher 1.66%, 0.78%, 2.87% and 0.78% sensitivity for the dataset of black spot, greening, canker and healthy, respectively, over the CNN method.

Table 5: Combined results for COA-CNN and CNN with respect to the datasets

Technique	FPR (%)	Specificity (%)	Sensitivity (%)	Accuracy (%)	Recognition Time (secs)
CNN	6.02	93.98	96.63	95.83	191.36
COA-CNN	4.22	95.78	97.41	96.92	124.54

Based on the above result, by utilising CNN with COA technique, it improves the accuracy, specificity, sensitivity, recognition time and FPR for the datasets used in this study. It can be implied that the COA-CNN approach yields a higher quality solution compared with the CNN approaches. This can be interpreted as the COA-CNN method produces a better quality solution in comparison with the CNN methods. Therefore, the COA-CNN technique achieved better performance than the CNN technique in all the metrics used when it came to detecting and classifying the citrus diseases.

CONCLUSION

This research evaluated COA-CNN using 1790 citrus images across four categories and showed improved accuracy, false positive rate, sensitivity, computational time, and specificity over CNN, confirming its effectiveness. It contributed to the development of a Coati Optimisation Algorithm-based CNN for citrus disease detection. The COA-CNN technique is recommended for addressing citrus disease detection challenges, and future work can explore integrating other feature extraction or hybrid optimisation algorithms like RSA and DMOA.

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