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Sugarcane Diseases Detection using the Improved Grey Wolf Optimization Algorithm with Convolution Neural Network

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Abstract: The Indian economy is heavily dependent on agriculture as most people have agriculture as their source of income. Therefore, Indian researchers must focus on the various challenges in this field. As there is huge diversity in the cultivation scenario in the different geographical locations of the country. However, sugarcane is one of the important crops grown in the country's major states. The major challenge other than climate change is the impact of plant diseases on the various crops. Various infections are caused by the different viruses and bacteria that lead to poor crop yield, leading to losses to farmers, which reflects losses to the country. The identification of the diseases is done by due inspection by experts in the fields; however, it is difficult for farmers to contact them, and their availability will be a challenge. Therefore, it is wise enough for the tools to be developed to extract the features from the images of the plant leaves and effectively identify the diseases. In this paper, a solution to the problem of disease identification is proposed with the help of the CNN model, the parameters of which are tuned using the grey wolf optimization neural network. The model based on IGWO is compared with the three other optimization algorithms, GWO, GA and PSO, out of which the IGWO and GA had the competitive result in accuracy comparison. However, the precision was better for PSO and GWO algorithms.

Introduction

Indian economy is widely dependent on agriculture. Sugarcane is one of the most popular crops and has had a major impact on our economy. It is not only the crop that can be used to satisfy the people's hunger. It has now become an important component of fuels as the fermentation of sugarcane can be processed to generate alcohol that can be blended into petrol and help reduce the import bills of the county. The quality of the crop yield is greatly affected by two important factors: environmental conditions, which are changing dramatically and cannot be changed by the farmers and the second factor that affects the crop yield is the health of the crop, which is mainly impacted by various viruses or bacterial infections. Experts monitoring plant leaves and stems could identify these infections easily, and timely actions could help achieve quality production. The process of identification of diseases is not easy as there are many diseases and knowledge of the expert is mandatory for the identification of the actual diseases as the farmers might identify the disease as wrong and could lead to the serious spread of diseases, thereby affecting the production. Bacterial or viral infections of the plants cause most diseases. Expert knowledge of plant diseases is not easily accessible to the farmers and hence, there is a need to bridge this gap with applications that can identify these diseases with a click and make the farmer confident and tension-free about crop diseases. Nowadays, researchers have made various attempts to generate models based on the deep neural network that

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could help identify crop diseases. Most of the models used the convolution neural network models for this process. The major challenge of such models is that either the model is too complex and may require a huge processing time, or the hyper-tuning of parameters itself becomes a huge problem. To overcome such challenges, this paper proposes an approach based on the grey wolf optimizer (GWO) that could help in the tuning of CNN parameters and even designing the neural network model to get effective results. The paper has been organized into five sections. In the first section, we introduce the problem. Section two discusses the various recent work done by the researchers. Section three describes the proposed approach. Section five presents and compares the results with the various existing approaches. Finally, the conclusion is drawn from the findings of the proposed approach.

Literature Review

In past the various studies have been presented that suggested the use of various machine-learning techniques for identifying diseases in sugarcane. Militante et al. (2019) suggest using deep neural networks to identify the plant leaf, indicating that the plant is a healthy plant or has some kind of infection. Similarly, Khan et al. (2017) suggested the use of the K Means clustering algorithm for the identification of plant diseases as the diseases imply the change in the color of leaves that can be easily identified as clusters of different color on the leaves and hence could help in the identification of the diseases (Khan et al., 2017). Srivastava et al. (2020) suggest the use of VGG16 Convolution Neural networks with different sets of classifiers like SVM, kNN, Neural network, logistic regression, SGD and Naive Bayes for identifying the diseases in the various sugarcane images. Ozguven et al. (2019) suggested the updated version of CNN for the identification of the leaf spot disease in sugar beet leaves. The model was trained and tested on the 155 images, and the Region-based CNN architecture was used to identify the diseases. Upadhye et al. (2023) studied the impact of artificial intelligence and machine learning on the various dimensions of plant life and how scientists use the CNN and other technologies and suggested using feedback mechanisms to get the most out of the generated models. They also suggested that the relationship between productivity and diseases in the plants can be studied in the future to avoid financial losses. Komol et al. (2023) suggested the use of YOLO version 8 in identifying the sugarcane diseases from the image datasets. They also suggested the use of robotics-based solutions to identify such plants, get the cure as soon as possible for the plants, and improve the productivity of the crop yield. Malik et al. (2021) studied both the CNN- and YOLO-based approaches. Finally, they identified that the CNN-based approach is better for identifying the plants' diseases than the YOLO-based approach. They suggested that diversity in the dataset could help achieve better results and automate the complete process. Hemalatha et al. (2022) have integrated the CNN-based approach into the Android-based application. So, that the complete end-user product for the farmers can be deployed. This would help get real-time feedback from the farmers and improve the approach. Kumar et al. (2021) suggested the use of Faster Region-based CNN, Region-based CNN and Single shot multi-box Detectors for feature detections. They have also suggested the use of YOLO models for the same to achieve good accuracy from their models (Kumar, 2021). Amarasingam et al. (2022) studied the various models like YoloV5, YoloR other deep learning models like faster R-CNN for the identification of the white leaf disease in the sugarcane but preferred the Yolo-based models on the fact that the memory required by the Yolv5 model is least in comparison of the other models which is suitable for their applications related to UAV's which will have less memory in comparison to the other models (Amarasingam et al., 2022). In another study, Murugeswari et al. (2022) suggested using the Faster CNN in Android applications to detect plant diseases as it is the amalgamation of image capturing and analyzing for the diseases.

Thilagavathi et al. (2020) suggested using various techniques for feature extraction like Adaptive Histogram Equalization (AHE), Principal component analysis and then extracted features are sent to the SVM classifier for the identification of the classes for the plant diseases.

The studies of various research articles suggest that the detection of the disease in sugarcane by the plant leaves images has been a prominent area of research in the past and the two most common approaches that have been used by researchers in the past are either relying on CNN or used the YOLO models for the image classification. Few researchers have also used other machine learning techniques like SVM, k means, and kNN in their studies. In all these studies, some researchers have given weight to the Yolo model because these models are to be deployed on low-end machines with very little storage. CNN models are usually heavier than Yolo models. In this study, based on the study, we are working on the following research question:

R1: Can we design the CNN model with a smaller number of weights and high accuracy?

R2: What is the various optimizers' impact on performance metrics?

To solve this problem, we came to know that this problem comes in the category of NP-hard problem as there is a huge search space in which the solution is to be identified. To do so, the most common technique is the heuristic-based optimization algorithm. The are several algorithms in the past have been used for searching for the optimal solution to problems, including the Genetic algorithm (Sun et al., 2020; Xie and Yuille, 2017; Ahmed et al., 2020) used the CNN and genetic algorithm for image classification problems that have been used to design the light weight CNNs and reduce the expertise required to design the CNNs. Similarly, the other set of algorithms termed Particle swarm optimization has been used in the past for generating the CNN models like cpso-CNN and has been claimed as efficient, which has helped in the hyper tuning of the parameters of CNN (Wang et al., 2019). In another study, a self-adaptive CNN was used to reduce the time required to identify the parameters of the CNN (Chen et al., 2021). A variant of GWO and CNN has also been used for the classification of videos with high accuracy and proved to be effective due to the fact of exploiting them effectively in both local and global search (Kumaran et al., 2018).

Proposed Approach

The grey wolf algorithm was proposed by Mirjalili et al. (2014), which is based on the hunting properties of grey wolves. In this approach, the wolves were categorised into four categories. These are alpha, beta, delta and Omega wolves. As the approach is based on the wolves' hunting behaviour, the wolves update their positions to hunt their prey. The basic operations given by Mirjalili et al. (2014) were classified into four basic operations.

1. **Searching the prey:** To perform the search for the prey, the wolves are initially placed randomly in the search space. The position of each wolf is represented by the $\overrightarrow{\mathrm{Xw}}$.
2. **Encirclement of the prey:** One the prey has been identified, the encirclement of the prey is done, mapping the relationship between the prey positions $\overrightarrow{\mathrm{Xp}}$ and wolf position $\overrightarrow{\mathrm{Xw}}$.

The new position of the wolf can be represented by the equation described by the equation 1

$$\overrightarrow{\mathrm{Xw}}(t+1) = \overrightarrow{\mathrm{Xw}}(t) - M.D \tag{1}$$

In the above equation, M is the coefficient matrix

M is the coefficient Matrix

$$\mathrm{D} = |\mathrm{K} \cdot \mathrm{X_p}(t) - \mathrm{Xw}(t)| \tag{2}$$

Where K=2*r

Here, r is a random vector in the range of 0 to 1

$$\mathrm{M} = 2\mathrm{p} - \mathrm{r}, - \mathrm{a} \tag{3}$$

Here, r' is a random vector generated in the range of 0 to 1

$$\mathrm{p} = 2 - t(\tfrac{2}{T}) \tag{4}$$

Here, t is the current iteration and T defines the total number of iterations.

3. **Hunting:**

Once the target has been defined, the mean partition of prey is defined as

$$\mathbf{X}\mathrm{p}(t+1) = \tfrac{1}{3}\mathbf{X_1} + \tfrac{1}{3}\mathbf{X_2} + \tfrac{1}{3}\mathbf{X_3} \tag{5}$$

The alpha, beta and omega wolves are updated relative to the relative position to generate the new positions as described by the equation below:

$$\begin{aligned} \mathbf{X}_1 &= \mathbf{X}_\alpha(t) - \mathrm{K}_\mathbf{1} \cdot \mathbf{D}_\alpha \\ \mathbf{X}_2 &= \mathbf{X}_\beta(t) - \mathrm{K}_\mathbf{2} \cdot \mathbf{D}_\beta \\ \mathbf{X}_3 &= \mathbf{X}_\delta(t) - \mathrm{K}_\mathbf{3} \cdot \mathbf{D}_\delta \end{aligned} \tag{6}$$

$\mathbf{D}_\alpha$, $\mathbf{D}_\beta$, $\mathbf{D}_\delta$ are given by relation.

$$\begin{aligned} \mathbf{D}_\alpha &= |\mathbf{C_1} \cdot \mathbf{X}_\alpha - \mathbf{X}| \\ \mathbf{D}_\beta &= |\mathbf{C_2} \cdot \mathbf{X}_\beta - \mathbf{X}| \\ \mathbf{D}_\delta &= |\mathbf{C_3} \cdot \mathbf{X}_\delta - \mathbf{X}| \end{aligned} \tag{7}$$

The IGWO-based CNN was generated using the proposed approach, and the algorithm for the same is described below in Figure 1.

The Neighborhood to the IGWO (Nadimi-Shahraki et al., 2021) elements are defined by equation 8 described below

$$\mathrm{R(t)} = \|\mathrm{X(t)} - \mathrm{Xp(t+1)}\| \tag{8}$$

The best result among the radius wolves' positions in different dimensions is compared and the same is selected. In Figure 1, the flowchart shows that all the images required for training and testing are provided to the GWO Algorithm. The GWO algorithm will generate an initial population of wolves that will be randomly positioned in search space. The position of wolves is equal to the dimension of the problem search space.

Table 1. Describes the Parameters Used in IGWO.

Sl. No.	Parameter	Value
1	Pop Size	5
2	Generation	5
3	Dimension	10

Based on the random population generated, the CNN is designed and trained to get the result once we get the result in terms of performance metrics (1-accuracy). This is used as the fitness value for GWO.

Using the fitness value, the alpha, beta, and gamma wolves are identified and moved towards prey that resides at the highest fitness level, that is Q. The process

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mentioned is an iterative process and continues to repeat until the total number of generations has not been completed. To do so, GenCount is updated after each generation. The GenCount >G is the threshold defined till now. The best solution will be stored in the alpha position of the array.

The parameters of IGWO are described in Table 1.

To tune the CNN Parameters in the 10 dimensions, the various parameters are mentioned in Table 2.

Table 2. Describes the parameters used for searching the hyperparameter for CNN.

	Hyper-parameter	Type	Selection
F1	[32,64]	int	0-1
F2	[64,128]	int	0-1
F3	[128,256,512]	int	0-2
K	[3,5]	int	0-1
A1	[relu, selu, elu]	int	0-2
A2	[relu, selu, elu]	int	0-2
D1	0.1 to 0.5	float	2 decimals
D2	0.1 to 0.5	float	2 decimals
Op	adamax, adadelta, adam, adagrad	int	0-3
Ep	50-100	int	51

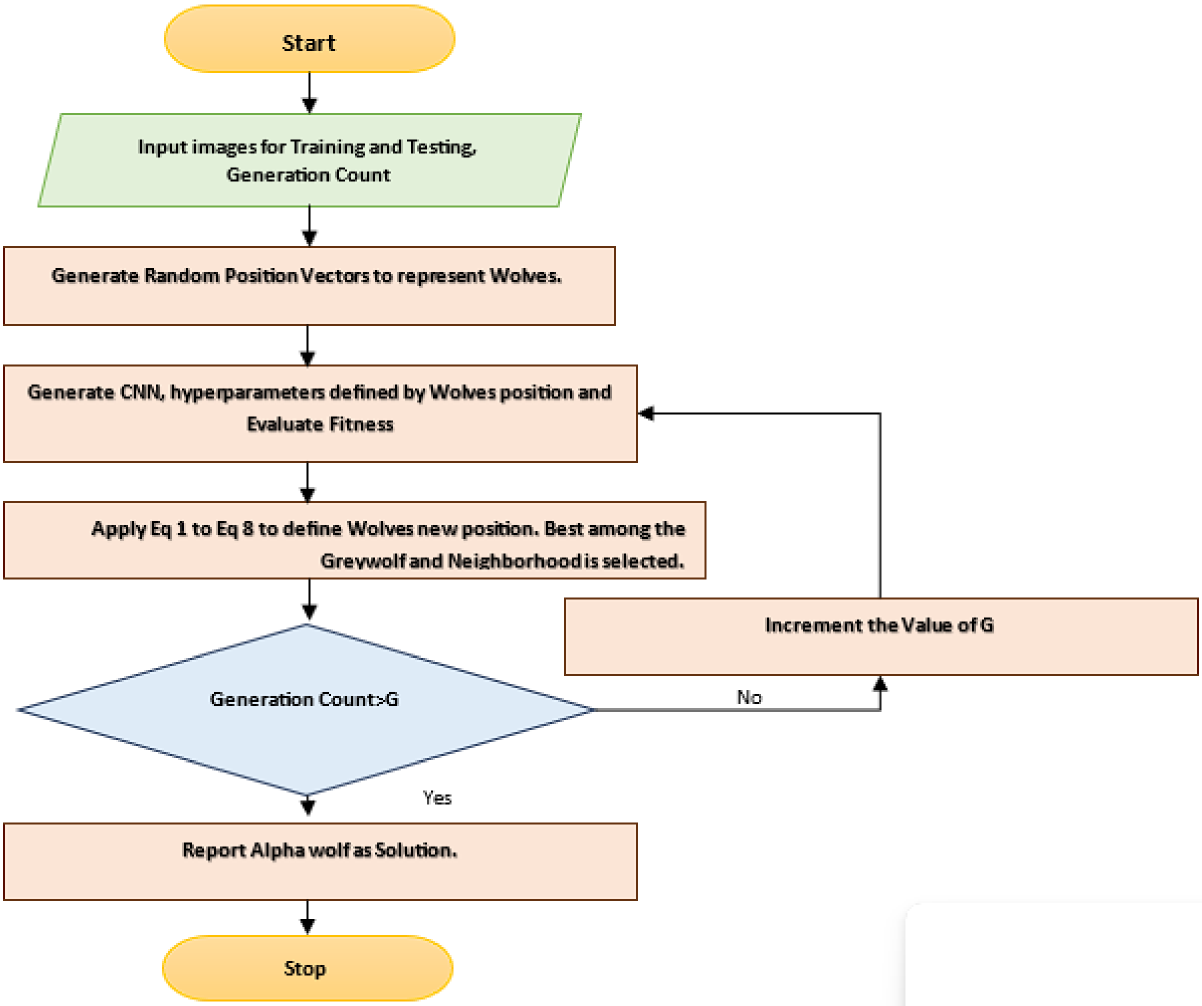

Figure 1. Describes the Flowchart of the proposed approach.

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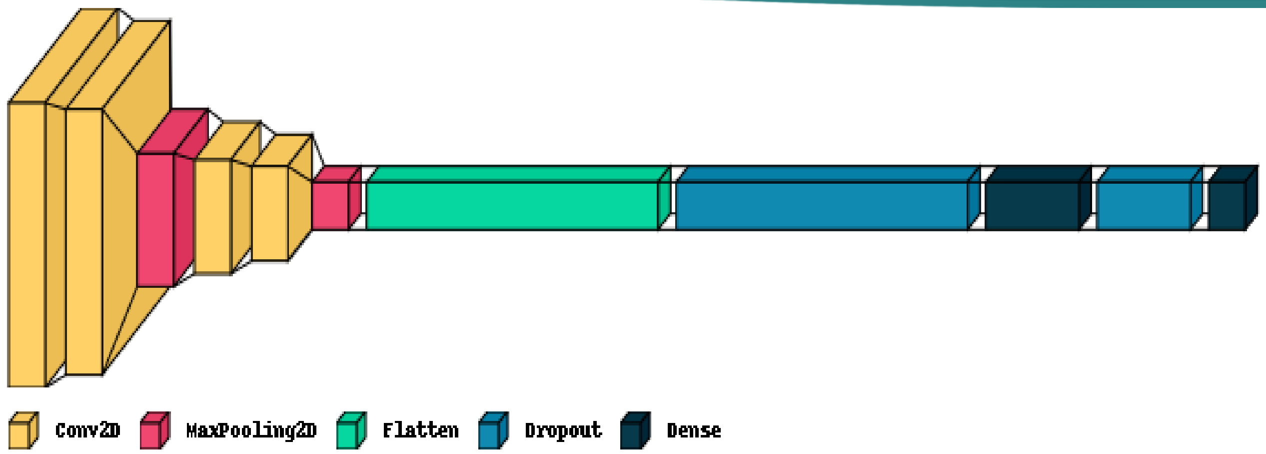

Figure 2. Describes the CNN model that is hyper-tuned using the GWO.

Table 3. Describes the comparison of the approaches on the various performance metrics.

Sno	Metrics	IGWO-CNN	GA-CNN	GWO-CNN	PSO-CNN
1	Accuracy	84.74	84.74	81.36	83.05
2	Precision	63.63	65	72.92	73.47
3	Recall	93.33	86.67	79.55	81.82
4	F1 Score	75.68	74.28	76.09	77.42

Table 4. Describes the confusion metrics of the GWO-CNN.

		Actual	
		Healthy	**Not Healthy**
Predicted	Healthy	13	7
	Not Healthy	2	37

These are the parameters that are used to tune the predefined CNN as described in Figure 2.

In Figure 2, the CNN model is described as hyper-tuned to get better results. Here in this CNN the First and Second layers are the Convolution layers and are tuned using the parameters F1, K, and activation function A1. The next layer after the convolution layer is the MaxPool layer. The fourth and Fifth layers are convolution layers with the different set of parameters F2, K and activation function A2. After which, the results are fed to the flattening layer and dropout layer, which further have the parameter d1.The result obtained is then sent to the dense network with activation function a2 and Filter f3. Finally, the results are flattened and sent to the dense layer with the SoftMax function to generate the actual class of the result. In the whole process, different parameterss are used and they can account for the 10 dimensions of search space with different values. This makes the search space very huge and hence becomes an NP-hard problem. Due to this, optimization algorithms like GWO can be used to identify the correct results.

Results and Discussion

To compare the GWO-CNN, we have considered the various models of CNN to compare the performance with the genetic-based CNN. We have used the dataset for sugarcane disease detection available on Kaggle (Mirjalili et al., 2014). The images were extracted and various argumentation operators were applied to generate the training and testing datasets which were used to train and test the proposed models. In the dataset, there were 4 classes of plant leaves, out of which 3 are different classes of diseases in plant leaves and one is the set of healthy leaves. The comparison of the same is described in Table 3, and the graph for the same is described in Figure 3. Figure 4 and Figure 5 describe the ROC curves of both approaches.

The proposed approach was tested on the image dataset and the confusion matrix for the same has been described in Table 4.

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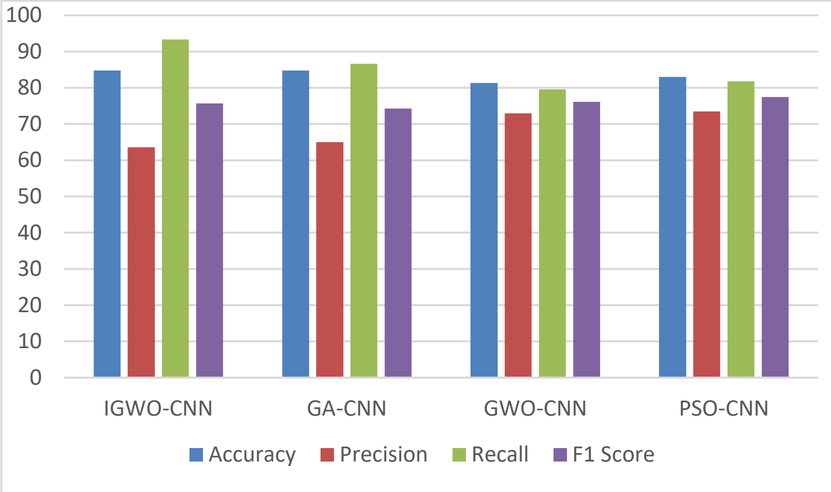

Figure 3. Describes the comparison of the approaches.

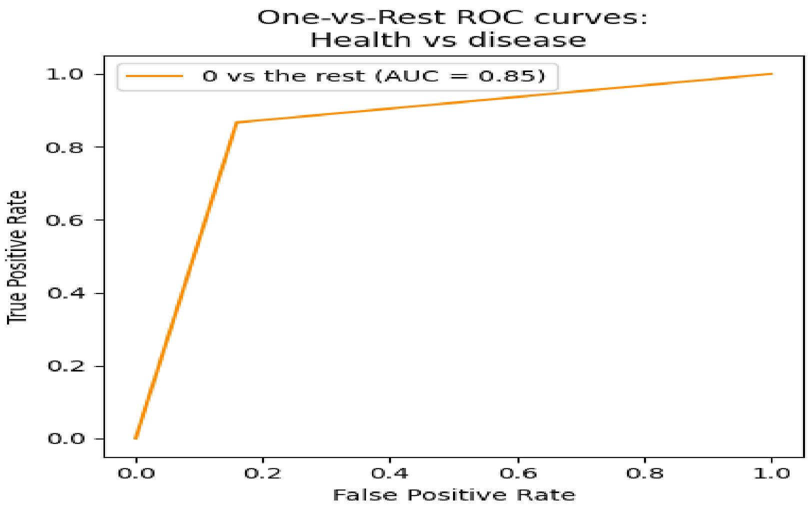

Figure 4. Describes the ROC curve for GWO-GA.

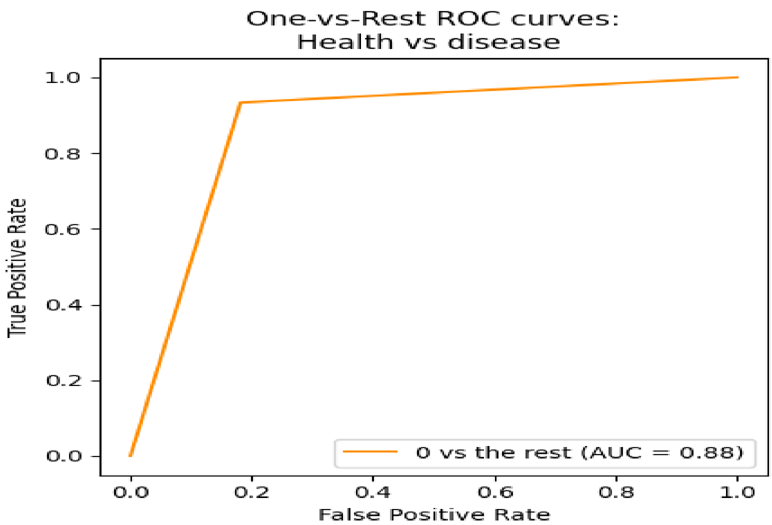

Figure 5. Describes the ROC curve for GWO-CNN.

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The above graph shows how the above algorithms have been working in the classification of whether the leaves of the sugarcane had diseases or not. This was stated as the 0 versus rest. In our dataset, we have considered three categories of diseases and a detailed comparison of the results for each is described in Figure 6.

function of the optimization function in such a way that all the performance metrics can be related and balanced so that better results can be obtained. Finally, it can be stated that proper hyper-tuning always results in good solutions, which were better than the results obtained by the complex models and had a huge amount of weight to be remembered.

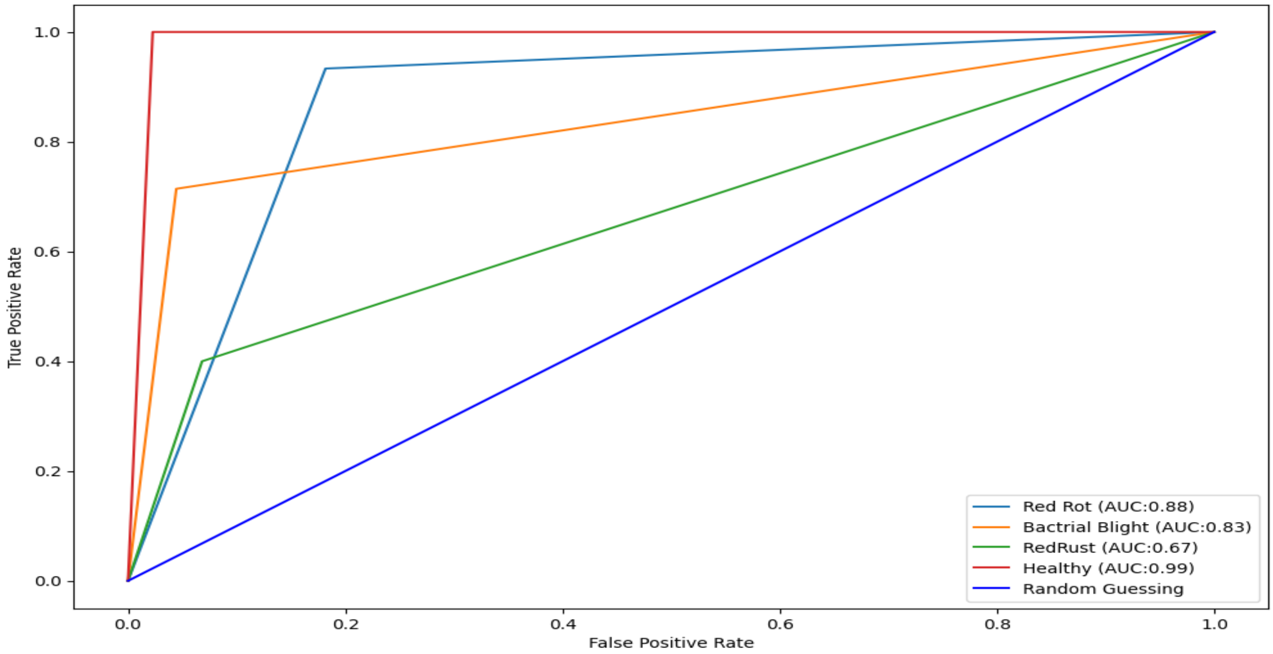

Figure 6. Describe the AUC of the three different types of diseases and healthy plant.

Conclusion and Future Work

The results generated using GWO-CNN and GA-CNN show that both approaches are efficient and have almost the same accuracy. However, the AUC for GWO-CNN is higher than GA-CNN by 3%. Similarly, GWO-CNN has higher recall and F1-score values. The recall was 6.67% higher for GWO-CNN and F1-Score was high by 1.4 %. However, GWO-CNN has less precision by 1.37 %, but F1-Score, which is used as a measure between precision and recall, is in favor of GWO-CNN. The approach answers that the simple CNN can be designed with a smaller number of layers that can have better accuracy. Hence, the optimization algorithm can help properly tune the parameters to generate better results. Another important observation is that the two variants of GWO, the improved IGWO, have a greater convergence rate based on the fitness function compared to other performance metrics considered directly as part of the performance metrics. Therefore, it can be concluded that even though the accuracy of the proposed approach is better, the other performance metrics may or may not offer better results. In the future, we can model the fitness

Conflict of Interest

The authors declare that there is no conflict of interest.

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