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A novel deep learning model with the Grey Wolf Optimization algorithm for cotton disease detection

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Abstract: Plants are a big part of the ecosystem. Plants are also used by humans for various purposes. Cotton is one of these important plants and is very critical for humans. Cotton production is one of the most important sources of income for many countries and farmers in the world. Cotton can get diseases like other plants and living things. Detecting these diseases is critical. In this study, a model is developed for disease detection from leaves of cotton. This model determines whether the cotton is healthy or diseased through the photograph. It is a deep convolutional neural network model. While establishing the model, care is taken to ensure that it is a problem-specific model. The grey wolf optimization algorithm is used to ensure that the model architecture is optimal. So, this algorithm will find the most efficient architecture. The proposed model has been compared with the ResNet50, VGG19, and InceptionV3 models that are frequently used in the literature. According to the results obtained, the proposed model has an accuracy value of 1.0. Other models had accuracy values of 0.726, 0.934, and 0.943, respectively. The proposed model is more successful than other models.

Keywords: Convolutional neural networks, Deep learning, Artificial intelligence, Cotton disease detection, Grey wolf optimization algorithm
Categories: I.2.1, I.2.10, I.3.8, I.4.9
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1 Introduction

Plants are the primary component of almost any ecosystem. All organisms get energy directly or indirectly from plants. It is essential to identify the infection in plant components such as leaves, stems, and natural products. Infections, microorganisms, and so forth cause leaf disorders. Typically, a farmer identifies leaf diseases by observing the leaf's spots, colour, and overall condition, but sometimes they need the assistance of professionals to identify diseased leaves or harvests [Sivakumar et al., 2021]. As a result of high population growth and a scarcity of water resources, the amount of land devoted to agriculture will continue to decrease globally. The plant's susceptibility to disease is one of the risks that must be evaluated at this stage. In contrast, plants are being separated from their native habitat and cultivated in unorthodox circumstances. Numerous important crops and plants are very susceptible to illness. They would have a difficult time surviving in nature without human intervention. Loss in crop yield is often attributable to plant disease or environmental variables such as climate, water resources, and nutrient accessibility. Environmental elements or product resources, such as temperature and humidity, are crucial for crop yield. The plant's root exudates, which improve the soil's nutritional content, play a vital function [Sohrab et al., 2014]. Compared to their relatives in the wild, cultivated plants are more disease-resistant. This refers to the enormous numbers of the same species or distinct species with a similar gene that have grown together, often across a distance of several kilometres [Kumar et al., 2021]. Plant disease refers to a collection of physiological, morphological, and pathological modifications in plants induced by biological or non-biological stimuli, which hinder normal functioning and also have a substantial impact on agricultural efficiency and financial benefits. As a result of globalization and climate change, plant diseases and predatory insects pose a greater threat to food security than ever before. Climate change has generated new favourable circumstances for the transfer of plant pests and diseases from their original habitat, which is accelerated by international commerce. Crop yields and food shortages may be caused by plant diseases that threaten global crop safety. The rapid detection and precise diagnosis of plant diseases are crucial for crop protection and preventing the spread of infections [Wang et al., 2021].

Cotton is recognized as the "White Gold" or "King of Fibers", enjoying a superior position among other cash crops and serving as the primary raw material for the thriving textile industry. It provides a living for around sixty million people. In addition, it is a key agricultural product that delivers economic returns to millions of farmers in both developing and wealthy countries [Prashar et al., 2019]. Cotton is a fibre crop that serves as a source of feed, biofuel production, staple, and oilseed harvest, providing 35% of the world's total fibre and raw material for textile manufacture [Zhang et al., 2013]. It is traditionally regarded as the most commercially important crop, but its output is affected by a variety of disease pathogens. Cotton is the most important fibre crop in the world, serving as the primary raw material for the cotton textile industry [Kumar et al., 2021]. However, there are certain issues with field crops, such as identifying the many diseases and pests that affect the crops and analyzing the nutritional deficiencies of plants. Despite the fact that each issue has its own relevance, the discovery of pests is the most vital so that appropriate action may be done to minimize damage. When a specific scenario emerges, farmers are alerted and take the necessary steps to handle the situation. When an agriculturist lacks accurate knowledge, he or she may waste time and money on ineffective pesticides and other ineffective management techniques. Additionally, it causes major agricultural problems. The diagnosis should be a skilled detective with keen observational abilities. Therefore, it is vital to maintain an open mind until all relevant details surrounding the issue have been gathered. Additionally, it must address the potential of many causative elements. In addition, illness causative agents and accurate disease classification are crucial to the efficacy of control methods. Consequently, disease diagnosis is the most essential component of a plant pathologist's education. In addition, if the disease-causing agent and illness are not properly identified, the management methods will result in the waste of money and time, as well as further plant losses. Therefore, accurate illness diagnosis is crucial. Otherwise, farmers may seek the assistance of agricultural technical specialists who will provide them with sound advice on how to boost crop yield and identify illnesses. However, farmers may encounter some common problems, such as the fact that the expert to whom they turn may not be able to provide relevant knowledge and information, or that they are unable to seek assistance due to long distances or because the agriculture expert is unavailable at the time of their visit [Prashar et al., 2019]. It is difficult to see with the naked eye that the cotton crop faces a number of problems due to illnesses that have a major impact on it. The plant's leaves are the most often affected by the virus. Eighty to ninety per cent of the plant's illnesses are found on its leaves. Therefore, this research focuses mostly on the leaf rather than the complete plant [Sivakumar et al., 2021].

As an advanced teaching area in recent years, image classification is one of the main aspects of computer vision and the foundation of several fields of visual recognition. The enhancement of classification network performance tends to considerably enhance its application level, including object detection [Liu et al., 2021], video classification [Savran Kızıltepe et al., 2021], human pose estimation [Song et al., 2021] etc. Improving image categorization technology is an essential component of advancing computer vision. Preprocessing image data, feature extraction and representation, and classifier creation are its primary processes. Image feature extraction, which is the foundation of image classification, has long been the focal point of research on image classification. Classification of images may be accomplished by learning classifiers capable of detecting the class/category of a given input picture and by developing class-specific features [Chen et al., 2021]. In recent years, a great deal of effort has gone into the development of automated systems for extracting basic picture properties. Convolutional neural networks (CNN) are an efficient approach for image classification that employs convolutional, pooling, and fully-connected layers throughout the learning process. Numerous applications exist, including image processing, computer vision, and pattern recognition. It is a kind of multi-layer neural network composed of neurons whose weights and biases may be trained [Momeny et al., 2021].

Real-world optimization issues have gotten increasingly difficult, necessitating more effective solution strategies. Different academics have investigated a variety of solutions to these complicated and demanding real-world situations. A portion of researchers uses conventional approaches to address these optimization challenges. Due to the nonlinear, nonproductivity features of the majority of real-world optimization problems, as well as the presence of several choice variables and complicated constraints, it is difficult to handle classical optimization problems using these methods efficiently. The advantages of the metaheuristic technique include independence from the problem model, independence from gradient information, robust search capabilities, wide applicability, and a good balance between solution quality and computation cost. Therefore, metaheuristic algorithms have been created to address real-world optimization problems [Gülmez and Kulluk, 2019, Xie et al., 2021, Gülmez, 2022c ,Gülmez, 2023, Gülmez, 2023a, Gülmez, 2023b].

There are many metaheuristic algorithms. Some of these are classical algorithms such as genetic algorithm and particle swarm optimization algorithm . Apart from these, researchers are developing new metaheuristic algorithms that are more advanced and give better results. GWO is one of them. The reason for choosing GWO is that it gives very successful results in mathematical functions, engineering problems, design problems and different optimization problems. It was chosen in this study because it is a successful algorithm [Mirjalili et al., 2014].

In this study, a novel deep-learning model is developed for the detection of diseases in cotton. The developed deep learning network is optimized with the Grey Wolf Optimization (GWO) algorithm. In this study, the GWO is used for the first time. The novelty of the study is that both a lightweight new network structure has been proposed and a new contribution to the literature has been made with network optimization with GWO.

In this study, a literature review has been made in Section 2. In Section 3, algorithms are explained. The algorithms include convolutional neural networks (CNN), GWO algorithm, and proposed network with GWO. In Section 4, firstly dataset is explained, evaluation metrics are introduced. Then the proposed model and ResNet50, VGG19, InceptionV3 models' results are introduced. All the results from the networks are compared. In Section 5, conclusion and ideas for future studies are proposed.

2 Literature Review

Prashar et al. [Prashar et al., 2019] proposed a solution to an agricultural challenge involving the identification of cotton leaf diseases using visual cues. They built the expert system for the identification of agricultural diseases in the provided picture dataset. Using artificial neural networks (ANN) with a variable layering strategy, overlapping pooling was used to categorise plant leaves for the identification of diseased and healthy leaves. The new ANN network model was used to dynamically modify the feature orientation in order to identify comparable dataset components. Support vector machine(SVM) and k-nearest neighbour(kNN) were used for the overlapping layer of classification in order to decrease errors via double-layered modelling. Their model utilised a combination of approaches, including pattern matching, morphological segmentation, and hue matching, to precisely identify the illness area with an accuracy of more than 96%.

Memon et al. [Memon et al., 2022] suggested a method based on meta-deep Learning for successfully identifying many cotton leaf diseases. They collected photos of cotton leaves from the field for their research. The collection included 2385 photographs of healthy and sick leaves. Using the data augmentation technique, the volume of the dataset was expanded. ResNet50, VGG16 Transfer Learning, Custom CNN, and their suggested model, the meta deep learning leaf disease diagnosis model, were trained on the dataset. A meta-learning approach was devised and used in order to achieve high precision and generalisation. The accuracy of their suggested model exceeded the Cotton Dataset by 98.53%.

Zekiwos and Bruck [Zekiwos and Bruck, 2021] worked on developing a model to improve the identification of cotton leaf diseases and pests using deep learning. They utilised prevalent cotton leaf diseases and pests, including leaf miner, spider mites, and bacterial blight. A K-fold cross-validation approach was used to partition the dataset and enhance the generalizability of the CNN model. For instructional reasons, roughly 2400 specimens (600 photos per class) were reviewed. In recognising leaf diseases and pests on cotton plants, their model obtained a 96.4% accuracy rate. This demonstrated the viability of its use in practical uses and the future need for IT-based technologies to supplement manual or conventional disease and pest detection.

Patil and Patil [Patil and Patil, 2021] concentrated on a novel deep learning approach that examines automatically identifying a diseased plant from leaf photos of the cotton plant and an IoT-based platform for gathering sensor data for detecting environmental changes. The deep CNN model was created to conduct cotton plant disease diagnosis utilising photos of the infected and healthy cotton leaf by collecting images during the whole training and validation process for image preprocessing; augmentation and fine-tuning. Various test cases were executed to evaluate the effectiveness of the designed system and make the new system inexpensive and self-sufficient. This newly developed technique made cotton plant disease detection as precise and effective as possible, hence enhancing crop productivity.

Sivakumar et al. [Sivakumar et al., 2021] intended to combine a section of agricultural land with the use of artificial intelligence in order to decrease plant leaf illness losses. In order to tackle this issue, they employed transfer learning models built using several CNN architectures, including ResNet152V2, InceptionV4, VGG19, and ResNet50. They conducted trials with these four approaches on the standard cotton leaves dataset in order to determine which strategy is superior at diagnosing cotton leaf diseases. Experiment findings showed that ResNet152V2 was 98.36% accurate. The most accurate of the models was ResNet152V2. Therefore, the concept of employing the transfer learning technique ResNet152V2 for plant disease identification proved extremely effective and also provided more accuracy.

Yadhav et al. [Yadhav et al., 2020] worked on the CNN algorithm-optimized real-time identification of plant diseases and their afflicted areas, so that proper fertilisers may be employed to avoid additional plant damage from pathogens. The activation function was the basis of the CNN classification model since it included non-linearity for a genuine artificial intelligence classification system. Alternative to Relu, a new mathematical activation function was designed and compared to current activation functions in order to enhance the system's performance and accuracy using a TensorFlow framework. The experimental findings on training databases demonstrated that the created activation function enhanced the accuracy and performance of the CNN model by 95%. The train speed of the CNN model was increased by 83%. Utilizing a K-means clustering approach, the additional disease-affected region was determined to optimise fertiliser application.

Noon et al. [Noon et al., 2021] proposed a simple but effective approach for identifying cotton leaf diseases based on deep learning. The suggested model was capable of reaching near-ideal precision with rapid convergence to reduce training costs. In addition to the healthy leaf images, a dataset encompassing three illnesses, namely curl virus, bacterial blight, and fusarium wilt, was obtained owing to the lack of publicly accessible datasets for this crop. These photographs were obtained via the Internet and the Southern Punjab area of Pakistan, where cotton is cultivated on thousands of acres annually and sold to Europe and the United States either as a raw material or as knitted industrial/domestic goods. Almost all iterations of their proposed deep learning architecture demonstrated remarkable recognition accuracy and precision in experimental tests.

Li and Yang [Li and Yang, 2020] introduced a few-shot cotton pest identification approach that only requires a little amount of raw training data, in contrast to most deep learning methods. The National Bureau of Agricultural Insect Resources (NBAIR) and a dataset containing natural settings were utilised to validate the efficacy and practicability of the few-shot methodology. CNN was applied to extract picture feature vectors. To guarantee the robustness of the system, the CNN feature extractor was trained using triplet loss to differentiate between distinct pest species. In addition, the few-shot recognition model is ultimately operational in an embedded terminal, using theconvolutional and max-pooling circuits created in the FPGA and the control software in the ARM. The running speed has reached 2 frames per second and may be increased by increasing hardware parallelism. The capacity of the suggested few-shot model to generalise was shown by the testing accuracy of 95.4% and 96.2% for the two datasets, respectively. In addition, their research may be seen as a successful effort to merge software and hardware for the implementation of intelligent algorithms in agricultural applications.

In this paper, in addition to the literature, a new deep CNN model is detected with GWO for cotton disease detection.

3 Algorithms

3.1 Convolutional Neural Networks

In the last decade, CNN has produced ground-breaking breakthroughs in a range of pattern recognition-related domains, including image processing and speech recognition. The most advantageous element of CNNs is their ability to reduce the number of parameters in ANN. This success has led both academics and developers to use bigger models to perform difficult tasks, which was not achievable with traditional ANNs; The most significant assumption regarding issues handled by CNN is that they should not have spatially dependent characteristics. The main difficulty is detecting them independent of their location in the photographs provided. Another crucial component of CNN is the acquisition of abstract characteristics when input propagates to deeper levels [Albawi et al., 2017]. A sample CNN can be seen in Figure 1.

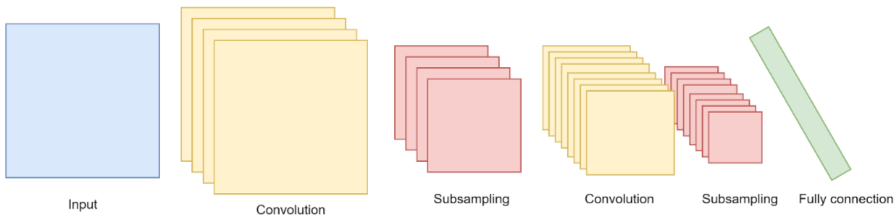

Figure 1: CNN [Gülmez, 2022a]

The convolution layer is a special type of linear operation used for the extraction of features in which a little matrix of numbers, known as a kernel, is applied to the input, which is a larger rectangular matrix known as a tensor. A feature map is obtained by calculating an element-wise multiplication between every item of the kernel and the input tensor at every point of the tensor and summing the results to generate the output value in the related place of the output tensor. This technique is repeated using several kernels to generate arbitrary feature maps, each of which represents a different property of the input tensors; hence, various kernels may be regarded as distinct feature extractors. Size and number of kernels are two essential hyperparameters that characterise convolution [Yamashita et al., 2018]. A sample convolutional layer can be seen in Figure 2.

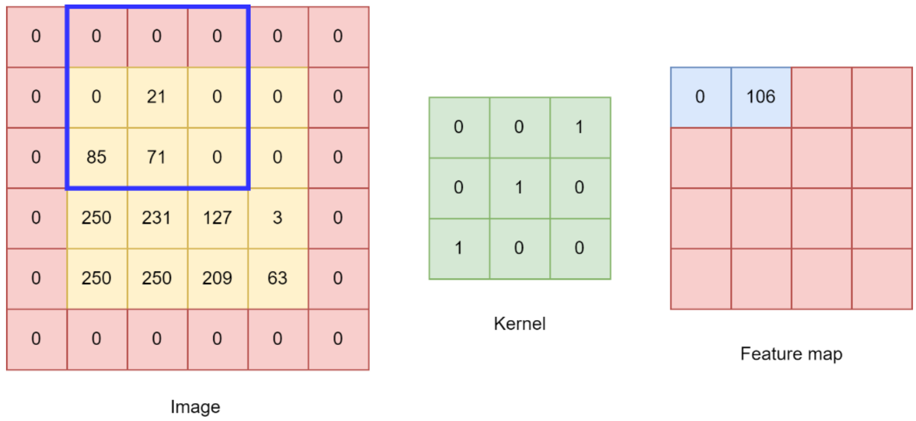

Figure 2: Convolution layer [Gülmez, 2022a]

The pooling layer offers a common downsampling procedure that decreases the size of the feature maps to provide translation invariance to tiny shifts and distortions and to minimise the number of following trainable parameters. Notably, none of the pooling layers has a trainable parameter, although filter size, stride, and padding are hyperparameters in pooling operations, comparable to convolution processes. The pooling layer generally is used in two types. The most used kind of pooling layer is max pooling, which takes patches from the input vectors, outputs the largest value at every patch, and dismisses the remaining values. In practice, a max pooling with a filter of size 2x2 and a stride of 2x2 is typically used. This reduces by a factor of 2 dimensions of feature maps. Unlike the width and height dimensions, the depth dimension of feature maps does not vary. Average pooling is another important pooling method. An average pooling is an extreme sort of downsampling in which a feature map with a size of height width is downsampled into a 1x1 array by averaging all the components within every feature map while retaining the depth of the feature maps. Typically, this step is performed just before the layers are entirely joined [Yamashita et al., 2018]. Figure 3 shows a sample pooling.

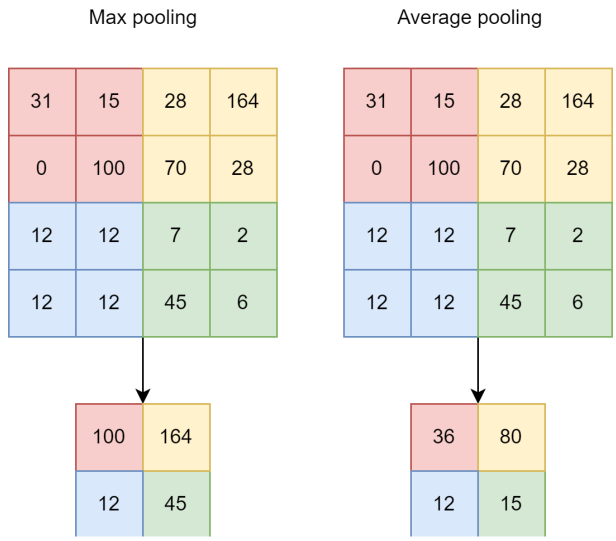

Figure 3: Pooling layer [Gülmez, 2022a]

Frequently, the output feature maps from the last pooling or convolution layer are flattened, converted to a 1D array of integers, and then linked to one or more dense layers, in which each input is directly coupled to each output by a trainable value. The final outputs of the network are mapped from the features recovered by the convolution layers and down-sampled by a sequence of fully connected layers in the pooling layers. Typically, a fully-connected layer contains as many output nodes as classes [Gülmez, 2021, 2022b]. Fully-connected layer, according to the explanation, is preceded by the function ReLU [Yamashita et al., 2018].

3.2 Grey Wolf Optimization Algorithm

GWO is an optimization algorithm inspired by grey wolves in nature. In GWO, there are three parameters. They are population size, iteration number, and a.

The grey wolf is an apex predator, which means that it is at the top of the food chain. The majority of grey wolves prefer to live in groups. The typical group size ranges from 5 to 12 members. As seen in Figure 4, they have a highly tight social dominating hierarchy, which is of great relevance [Mirjalili et al., 2014].

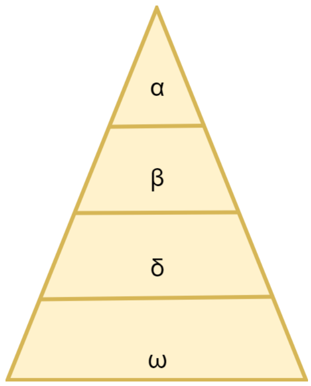

Figure 4: Grey wolf hierarchy [Aziz et al., 2019]

Alphas are the male and female leaders of the group. The alpha is primarily responsible for making judgments on hunting, sleeping location, wake-up time, etc. The choices of the alpha are dictated to the group. Nonetheless, a kind of democratic behavior has also been seen when an alpha leads the other wolves in the group. The whole group recognizes the alpha by lowering their tails during group meetings. The alpha wolf is also known as the dominating wolf since the group must obey its commands. The alpha wolf is permitted to mate solely inside the group. Intriguingly, the alpha is not always the strongest member of the group but rather the greatest at controlling the group. This demonstrates that a group's structure and discipline are far more essential than its strength [Mirjalili et al., 2014].

Beta is the second level of the grey wolf social hierarchy. The betas are subordinate wolves who assist the alpha in making decisions and participating in other group activities. The beta wolf may be male or female, and in the event that one of the alpha wolves dies or gets extremely old, it is likely the best contender to become the alpha. The beta wolf should revere the alpha but should also command the lower-ranking wolves. It serves as the alpha's counselor and the group's disciplinarian. The beta reinforces the alpha's directives throughout the group and provides the alpha with feedback [Mirjalili et al., 2014].

Omega is the lowest-ranked grey wolf. The omega serves as the scapegoat. Omega wolves must always defer to all other dominant wolves. They are the last wolves permitted to eat. It may seem that the omega is not a significant member of the group, yet it has been found that the loss of the omega causes internal strife and troubles for the whole group. This is due to the omega releasing the aggression and anger of all wolves. This helps satisfy the whole group and preserve the hierarchy of power [Mirjalili et al., 2014].

If a wolf is not an alpha, beta, or omega, such a wolf is referred to as a delta. They must bow to alphas and betas, but they are dominant over omegas. This group includes scouts, sentinels, elders, hunters, and caretakers. Scouts are responsible for monitoring the territory's borders and alerting the group of any impending threat. Sentinels defend and ensure the group's safety. Elders are the seasoned wolves that were once alpha or beta. Hunters assist the alphas and betas in hunting animals and supplying the group with food. The caretakers are responsible for tending to the group's sick, injured, and sick wolves [Mirjalili et al., 2014].

GWO is inspired by the grey wolf hunting process. During the hunt, grey wolves surround the prey. To represent encircling behavior quantitatively, equations (1) and (2) represent it. A and C vectors can be calculated as (3) and (4).

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{2}$$

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{3}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{4}$$

t represents the current iteration. Xp is the position vector of the prey, while X is the position vector of a grey wolf. The random integers r1 and r2 are between 0 and 1. a decreases linearly from 2 to 0 during the repetitions. A and C are coefficient vectors. Grey wolves are able to detect the position of their prey and surround them. Typically, the search is led by the alpha. The beta and delta may also sometimes engage in hunting. However, in an abstract search space, the optimal solution's position is unknown. To mathematically imitate the hunting behaviour of grey wolves, we assume that the alpha that is the best solution, beta, and delta possess superior information about the likely location of prey. Therefore, we save the top three best solutions found so far and require the other search agents to update their positions based on the best search agents' locations. In this respect, the following formulae are proposed:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|, \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \tag{5}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \tag{6}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{7}$$

Figure 5 shows how a search agent changes its location in a 2D search space according to alpha, beta, and delta. It is observable that the end location would be arbitrary inside a circle given by the positions of alpha, beta, and delta in the search space. In other words, alpha, beta, and delta estimate the location of the prey, while other wolves randomly adjust their positions around the prey.

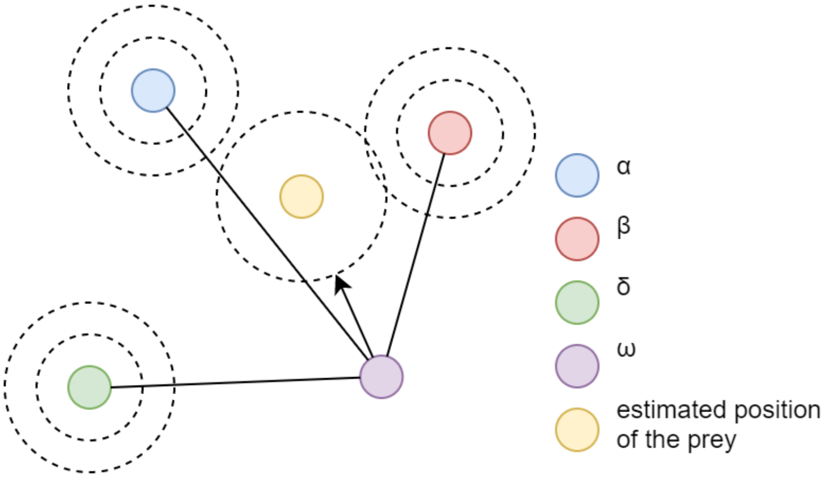

Figure 5: Position updating [Mirjalili et al., 2014]

In this study, GWO is used to find the best architecture of the deep CNN model for detecting cotton leaf diseases. The parameters of the GWO used in this study are population size=50, iteration number=50, and a= from 2 to 0, linearly decreasing. In the first iteration, a=2, and in the last iteration, a=0. It is recommended in the GWO paper [Mirjalili et al., 2014]. The Pseudo code of the algorithm is shown in Table 1.

```
Initialize the grey wolf population
Initialize a
Calculate A and C related to a
Calculate the fitness function for every wolf
X_alpha = the best wolf
X_beta = the second best wolf
X_delta = the third best wolf
While (iteration t from 0 to iteration number)
        For every wolf
                Update the position of the wolf
        Update a
        Calculate A and C
        Calculate the fitness function for every wolf
        Update X_alpha, X_beta, X_delta
        t = t + 1
return X_alpha
```

Table 1: Cotton disease dataset

3.3 Proposed Model

The main framework of the network has a total of thirteen layers. The input image size is (224, 224, 3). It is widely utilised in CNN models. After the input, a convolutional layer exists. The next layer is a maxpooling layer. The following layers are convolutional and maxpooling. Then follow additional convolutional and maxpooling layers. Next comes a convolutional layer. The output is then flattened. After flattening, a dropout layer is obtained. Then comes a dense layer. Then a dropout layer follows. The output of the network is a dense layer with multiple nodes. The number of classes equals the number of nodes. *Figure 6* represents the framework of a deep CNN. GWO algorithm determines the optimal layer parameters.

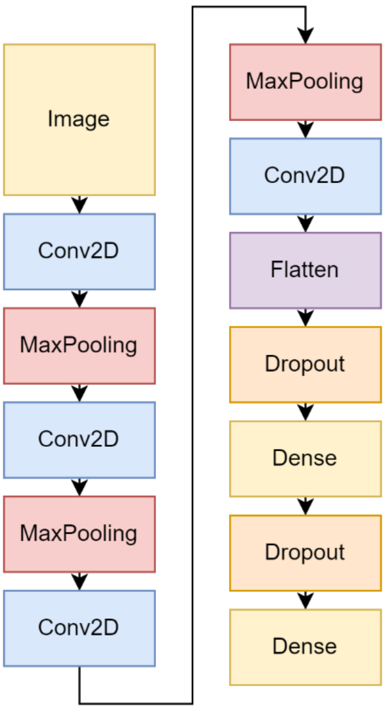

Figure 6: Deep CNN general structure

In this study, GWO is used for the deep CNN model architecture. First, a deep CNN model is created with the values from the GWO algorithm. These deep networks are then trained and tested with the dataset used to understand whether cotton leaves have diseases. An error rate is determined for each network. This solution with a low error rate is a valuable solution. Then, these evaluated solutions are processed through the GWO algorithm throughout the iterations. With each iteration, new networks are created, and more and more successful results are obtained. The flowchart of the algorithm is in Figure 7.

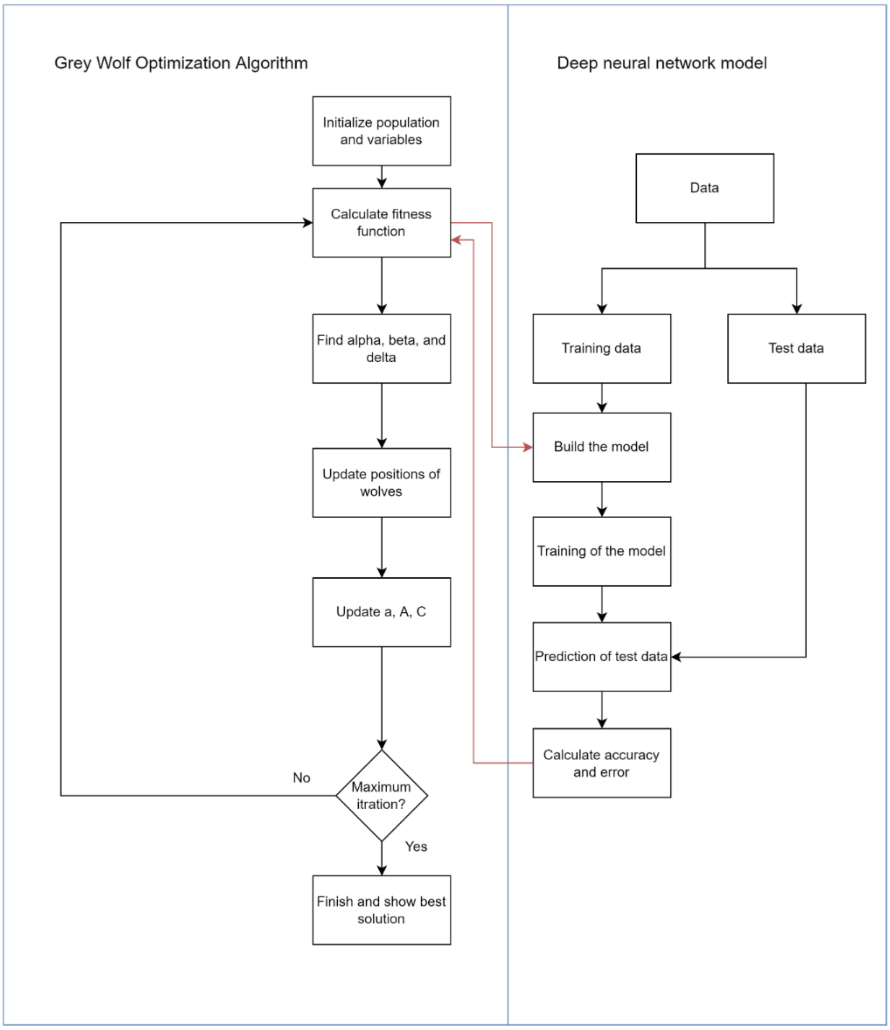

Figure 7: Flowchart of the proposed model

4 Results and Discussion

4.1 Dataset

In this study, a cotton disease dataset is used. It has four classes. They are diseased cotton leaf, diseased cotton plant, fresh cotton leaf, and fresh cotton plant. Every class has images. The diseased cotton leaf has 288 train images, 25 test images, the diseased cotton plant has 815 train images, 28 test images, the fresh cotton leaf has 427 train images, 26 test images, and the fresh cotton plant has 421 train images, 27 test images. The distribution of the dataset is in Table 2.

Class	Diseased cotton leaf	Diseased cotton plant	Fresh cotton leaf	Fresh cotton plant	Total
Train	288	815	427	421	1951
Test	25	28	26	27	106
Total	313	843	453	448	2057

Table 2: Cotton disease dataset

An example image of every class is shown in Figure 8.

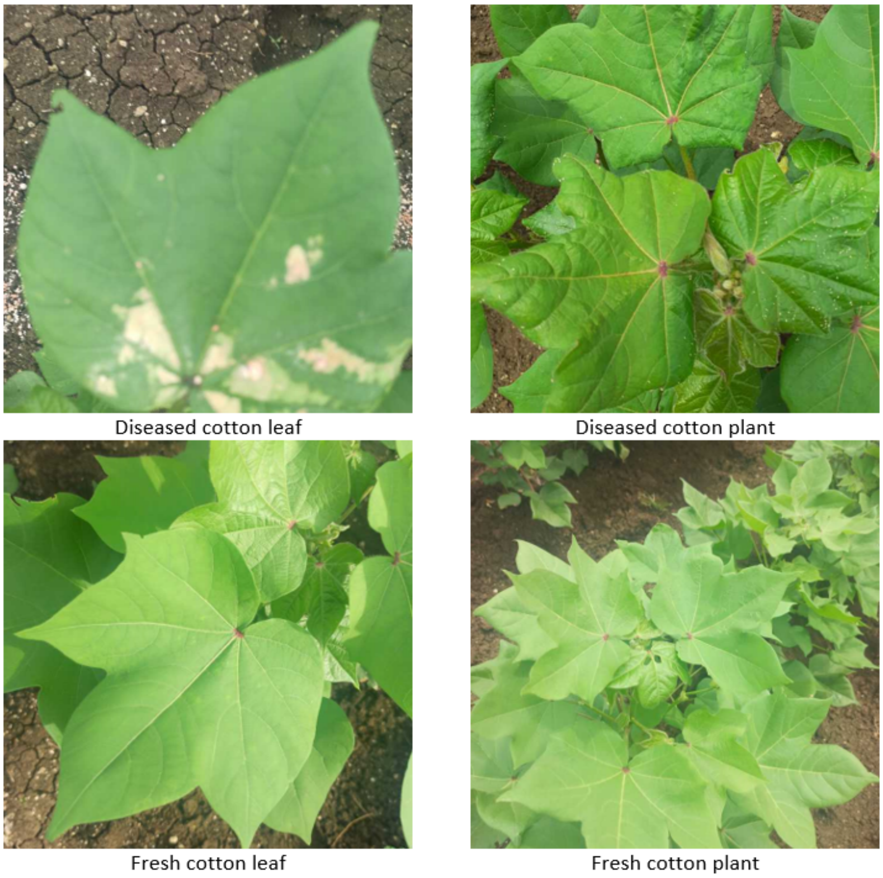

Figure 8: Sample images from the dataset

4.2 Evaluation Metrics

Evaluation metrics that are used in this paper are accuracy, precision, recall, and F1 score. The metrics are used very commonly for classification problems. Also, for the GWO algorithm, the error rate that is misclassed ratio is used. The accuracy, precision, recall, F1 score, and error rate formulas can be seen in (8), (9), (10), (11), and (12) respectively [Gülmez, 2022c, 2023b].

$$accuracy = \frac{true\,positive + true\,negative}{true\,positive + true\,negative + false\,positive + false\,negative} \quad (8)$$

$$precision = \frac{true\,positive}{true\,positive + false\,positive} \quad (9)$$

$$recall = \frac{true\,positive}{true\,positive + false\,negative} \quad (10)$$

$$F1\,score = \frac{2 * recall * precision}{recall + precision} \quad (11)$$

$$error\,rate = 1 - accuracy \quad (12)$$

The alternatives are prepared to create model architecture. These are the number of filters, the shape of filters, the training algorithm, the learning rate of the training algorithm, the size of the dense layer, and the dropout rate of the dropout layer. The alternatives can be seen in Table 3. GWO tries to find the best architecture for the neural network. Every convolutional layer has 2 variables, pooling layer has 1 variable, dropout layer has 1 variable, dense layer has 1 variable, training algorithm is 1 variable and learning rate is 1 variable. So, in this paper, the proposed model will be found by 16 variables.

Parameters	Alternatives
Number of filters	4, 8, 16, 32, 64, 128
Shape of filters	(1,1), (2,2), (3,3), (4,4), (6,6), (5,5), (7,7), (8,8)
Shape of pooling	(2,2), (3,3)
Training algorithm	Adagrad, Adam, Adamax, RMSprop, SGD
Learning rate	0.01, 0.001, 0.0001, 0.00001, 0.000001
Size of the dense layer	4, 8, 16, 32, 64, 128, 256, 512, 1024
Dropout rate	0.3, 0.4, 0.5, 0.6, 0.7

Table 3: Alternatives of the neural network model

4.3 Proposed Model

The proposed model is optimized by GWO algorithm. GWO algorithm is used with 50 iteration and 50 population size. The convergence plot can be seen in Figure 9. In the first iterations the average values and standard deviation values are similar. But at the last iterations they are increasing. The accuracy of the model goes to perfect, especially after the 41. iteration.

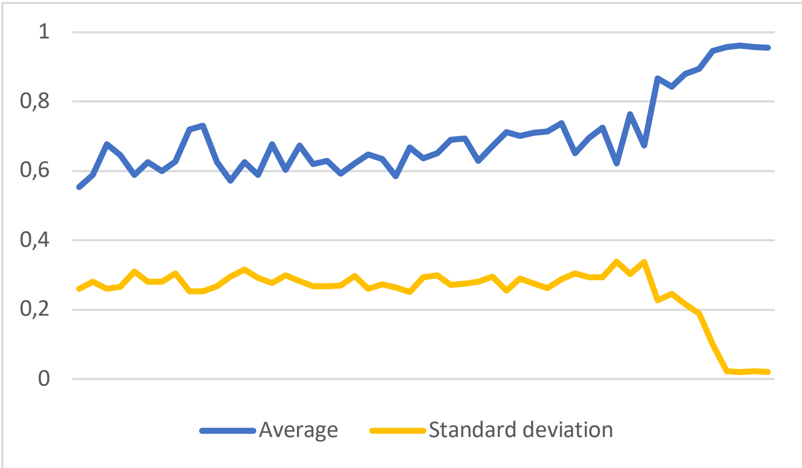

Figure 9: Convergence plot

In Figure 10, the loss function changes depending on the iterations for the proposed model. This value is constantly decreasing for training data. For test data, however, it decreases in a fluctuating fashion. In the last iteration, the values are very close to zero.

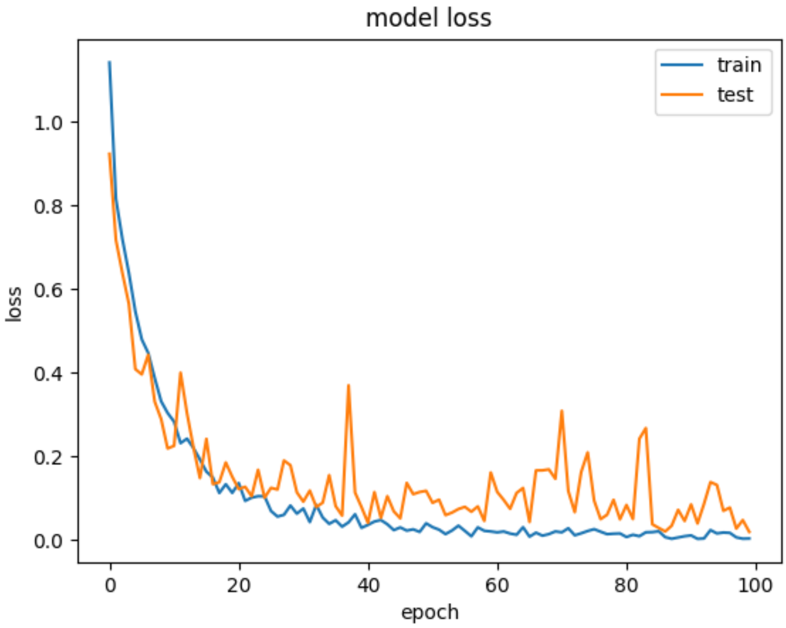

Figure 10 Loss function of the proposed model

Figure 11 shows that the accuracy value has increased continuously. It is slightly more fluctuating in the test data than in the training data. By the last iteration, accuracy reaches 1. This shows that all classes are predicted correctly.

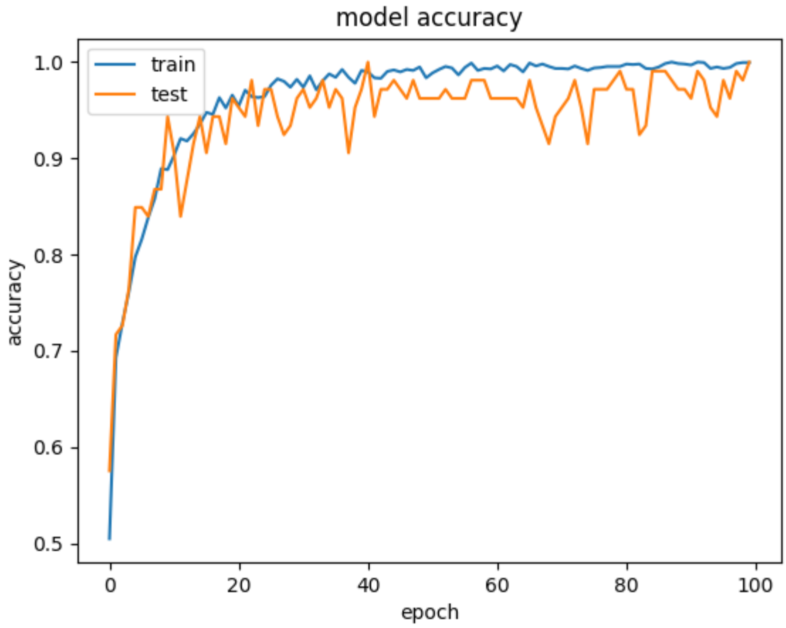

Figure 11: Accuracy result of the proposed model

Figure 12 shows that the predictions are correct for all classes. It is a very successful model.

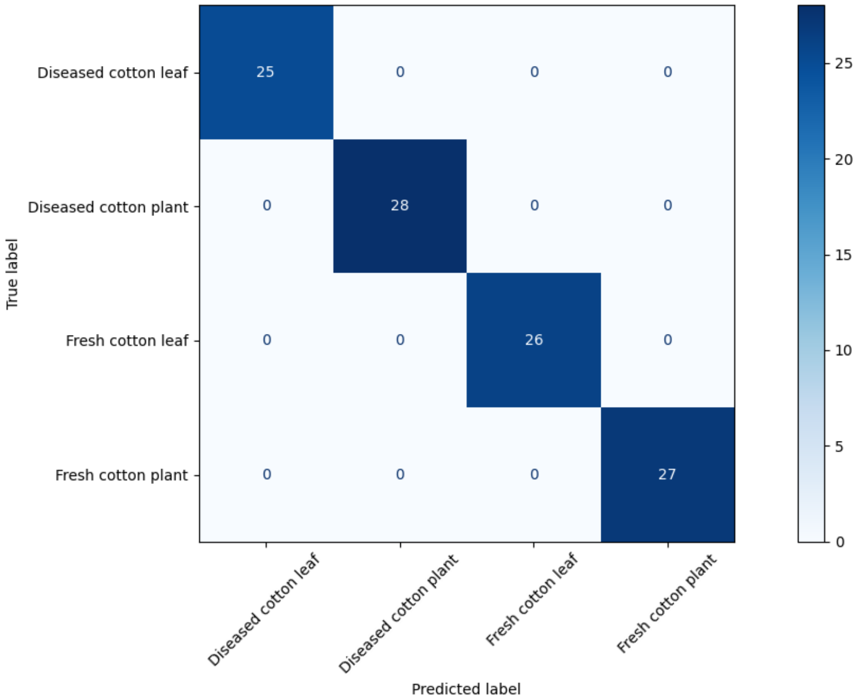

Figure 12: Classification result of the proposed model

Table 4 shows that the proposed model gives 1 accuracy. So it gets all the predictions right. Therefore, precision, recall, and F1-score are also equal to 1.

Class	Precision	Recall	F1-score	Support
Diseased cotton leaf	1.000	1.000	1.000	25
Diseased cotton plant	1.000	1.000	1.000	28
Fresh cotton leaf	1.000	1.000	1.000	26
Fresh cotton plant	1.000	1.000	1.000	27
Accuracy			1.000	106
Macro-average	1.000	1.000	1.000	106
Weighted-average	1.000	1.000	1.000	106

Table 4: Performance of the proposed model

4.4 ResNet50

Figure 13 shows that the loss values for the ResNet50 model have gradually decreased.

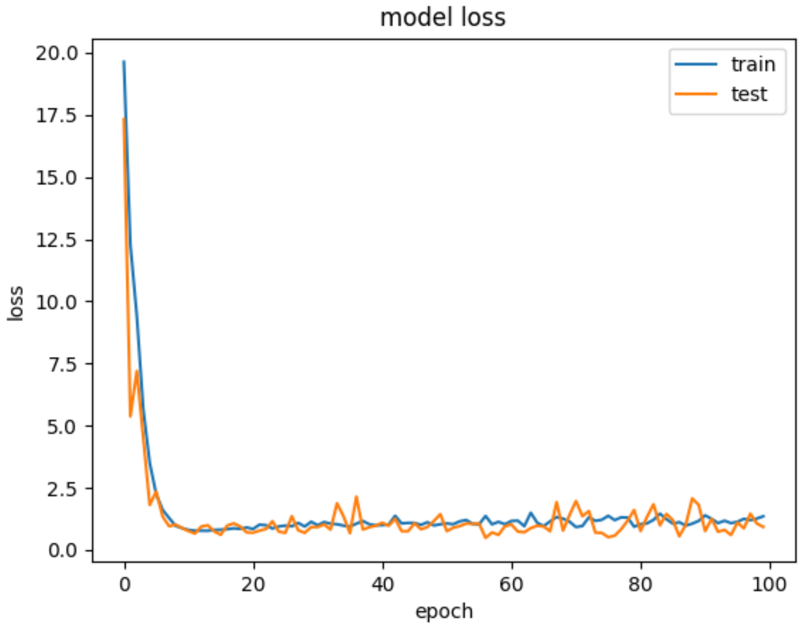

Figure 13: Loss function result for the ResNet50 model

Figure 14 shows that accuracy increases as the iterations progressed until the twentieth iteration, but after the twentieth iteration, this increase almost stops. It continues very volatile and uncertain for test data.

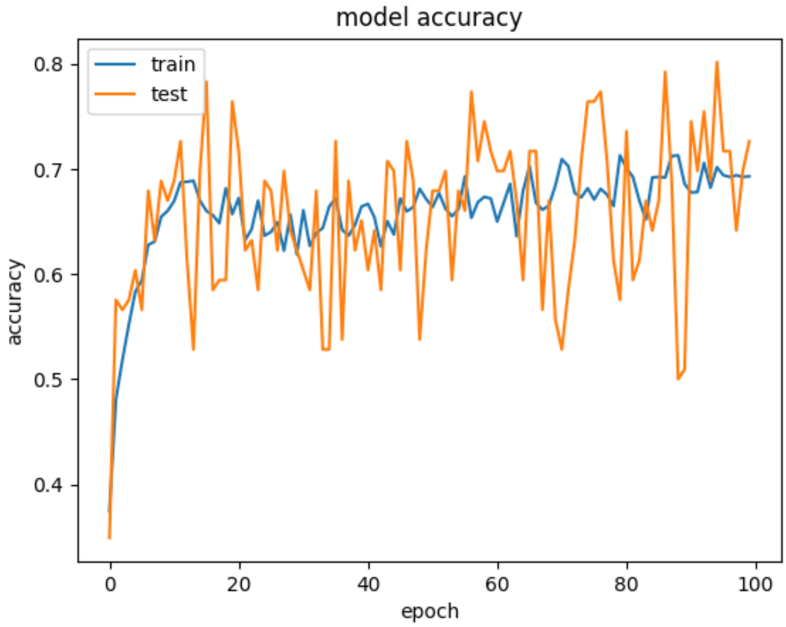

Figure 14: Accuracy result for the ResNet50 model

Figure 15 shows that good results are obtained in fresh cotton leaf and fresh cotton plant classes. But the results in other classes are worse.

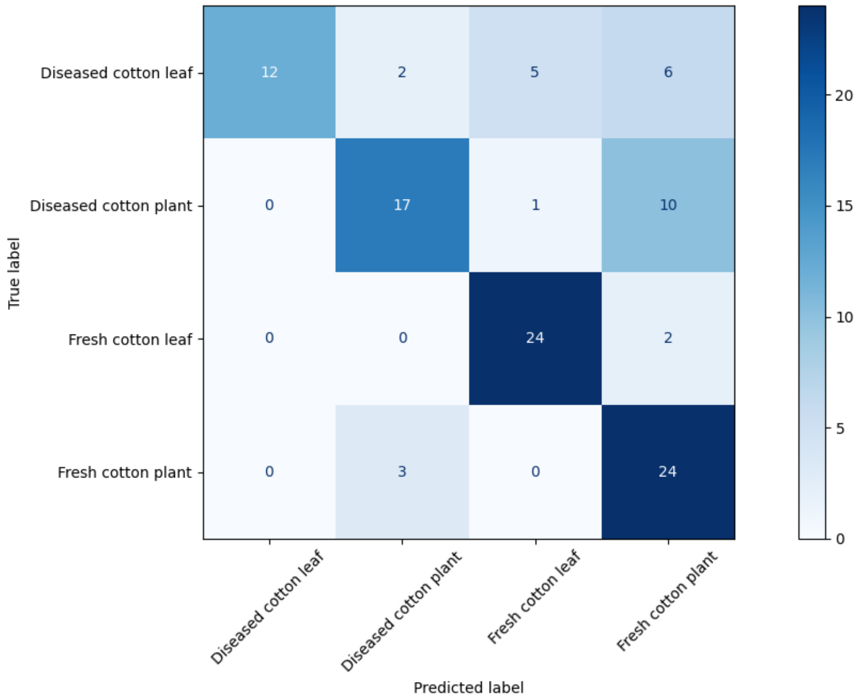

Figure 15: Classification results for the ResNet50 model

Table 5 shows that the ResNet50 model gives an accuracy of 0.726. In addition to this result, it gives 0.782 precision, 0.726 recall and 0.720 F1-score results.

Class	Precision	Recall	F1-score	Support
Diseased cotton leaf	1.00	0.480	0.649	25
Diseased cotton plant	0.773	0.607	0.680	28
Fresh cotton leaf	0.800	0.923	0.857	26
Fresh cotton plant	0.571	0.889	0.696	27
Accuracy			0.726	106
Macro-average	0.786	0.725	0.720	106
Weighted-average	0.782	0.726	0.720	106

Table 5: Performance of the ResNet50 model

4.5 VGG19

Figure 16 shows that the loss function value for the VGG19 model has decreased for the training data. For the test data, it continues in a very scattered way.

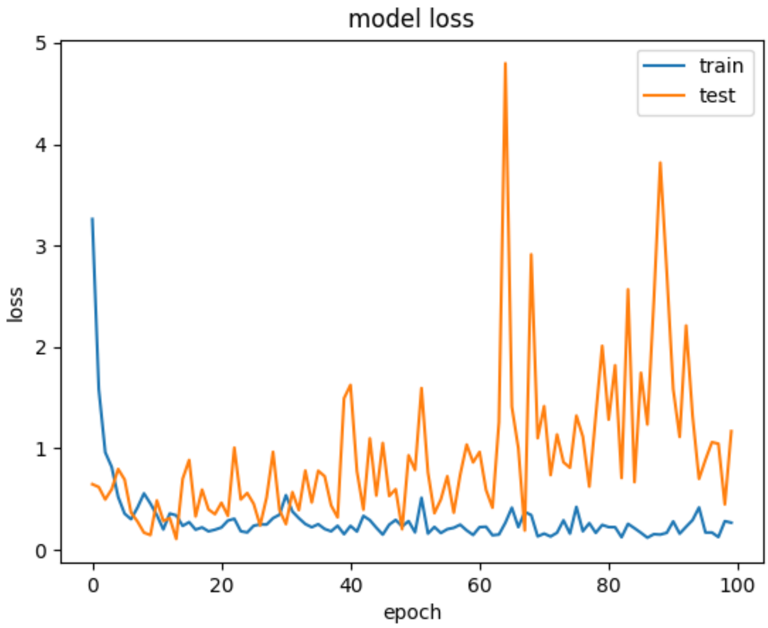

Figure 16: Loss function result for the VGG19 model

Figure 17 shows that the accuracy value has gradually increased for the training data. However, it cannot be said that it continues in the same way for the test data.

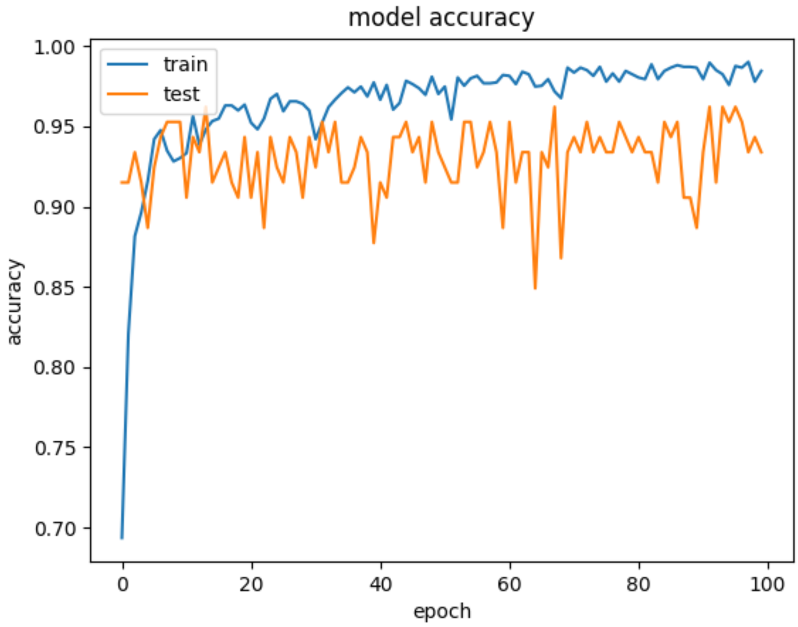

Figure 17: Accuracy result for the VGG19 model

Figure 18 shows that the fresh cotton plant performs poorly in its class. The success rate in other classes is high.

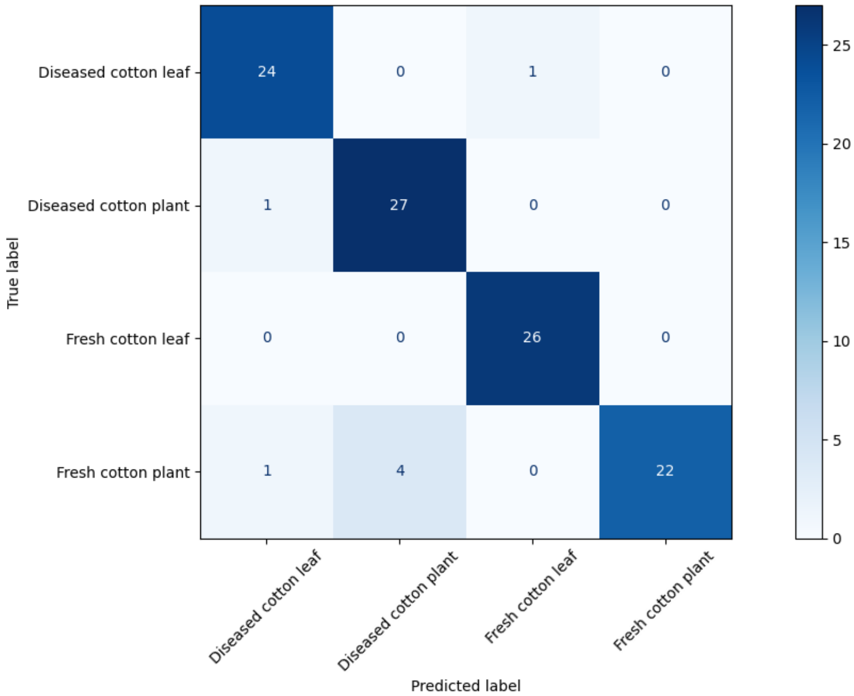

Figure 18: Classification result for the VGG19 model

Table 6 shows that the VGG19 model gives an accuracy value of 0.934. It also has 0.939 precision, 0.934 recall, and 0.933 F2-score.

Class	**Precision**	**Recall**	**F1-score**	**Support**
Diseased cotton leaf	0.923	0.96	0.941	25
Diseased cotton plant	0.871	0.964	0.915	28
Fresh cotton leaf	0.963	1.000	0.981	26
Fresh cotton plant	1.000	0.815	0.898	27
Accuracy			0.934	106
Macro-average	0.939	0.935	0.934	106
Weighted-average	0.939	0.934	0.933	106

Table 6: Performance of the VGG19 model

4.6 InceptionV3

Figure 19 shows that the loss function for InceptionV3 shows progressively lower values in the training data. The test data shows irregularity.

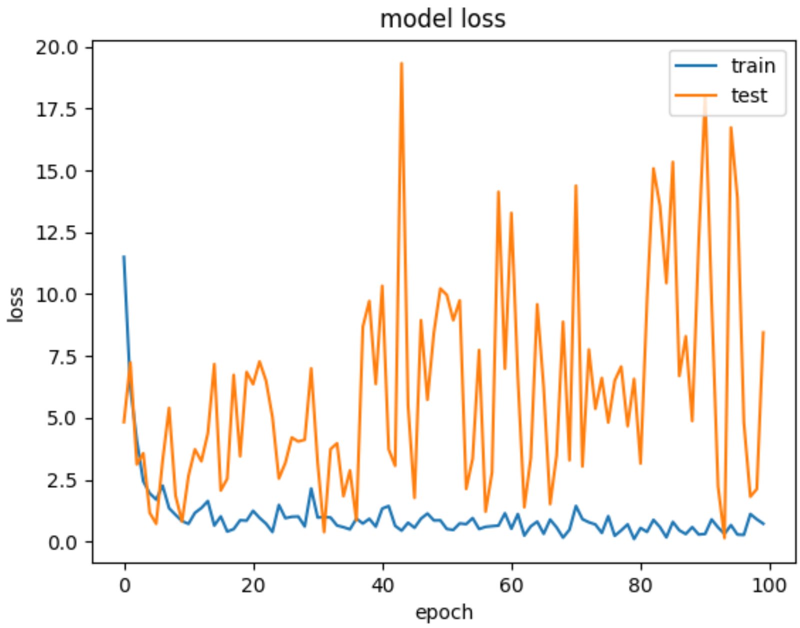

Figure 19: Loss function result for the InceptionV3 model

Figure 20 shows that the accuracy value has increased continuously for the training data. For the test data, it continues in a scattered manner.

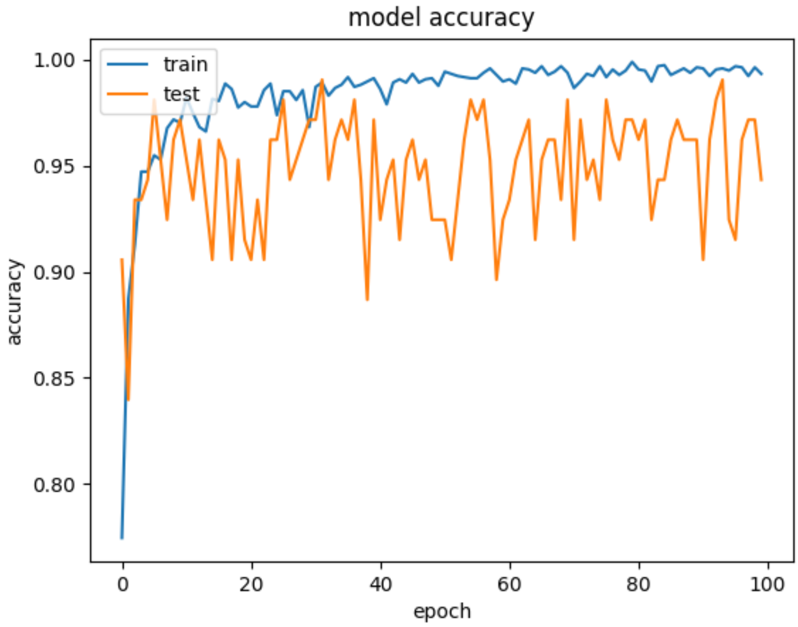

Figure 20: Accuracy result for the InceptionV3 model

Figure 21 shows low successful results for the fresh cotton plant class. High accuracy is achieved for other classes.

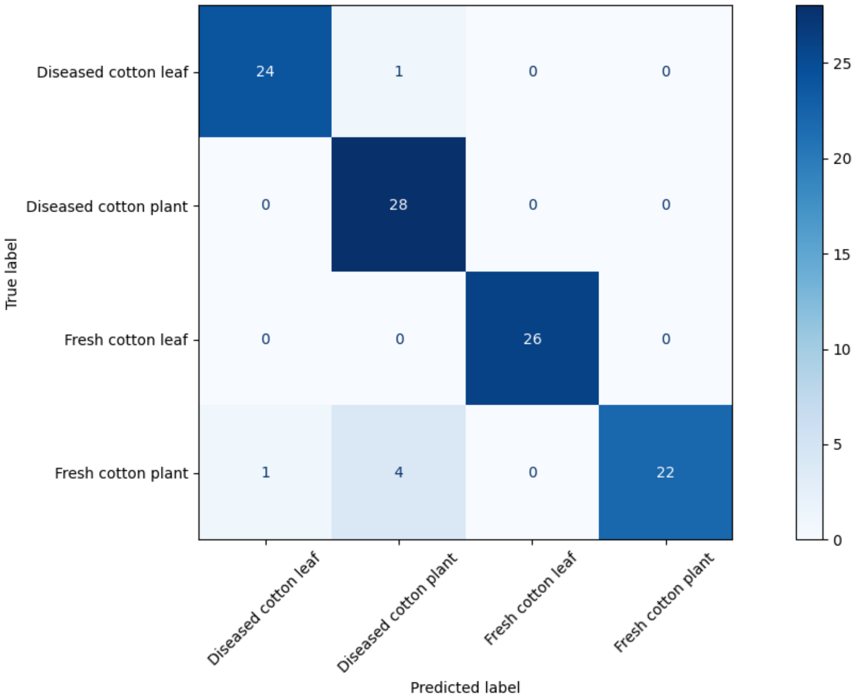

Figure 21: Classification results for the InceptionV3 model

Table 7 shows the InceptionV3 model has an accuracy of 0.943. It also has 0.951 precision, 0.943 recall, and 0.943 F1-score.

Class	Precision	Recall	F1-score	Support
Diseased cotton leaf	0.960	0.960	0.960	25
Diseased cotton plant	0.848	1.000	0.918	28
Fresh cotton leaf	1.000	1.000	1.000	26
Fresh cotton plant	1.000	0.815	0.898	27
Accuracy			0.943	106
Macro-average	0.952	0.944	0.944	106
Weighted-average	0.951	0.943	0.943	106

Table 7: Performance of the InceptionV3 model

The proposed model is optimized by GWO. The optimized network gives 1.0 accuracy. But it is only one result. To compare more fairly, all the models should be run lots of times, and they should be compared. So, the proposed model and the other models are run 30 times, and the results are received. Getting results 30 times shows a normal distribution effect due to the central limit theorem. The results can be compared as fairer. The accuracy results are shown in Table 8.

Model	Average	Standard deviation	Maximum	Minimum
Proposed model	0.968	0.021	1.0	0.934
ResNet50	0.710	0.048	0.802	0.613
VGG19	0.937	0.018	0.972	0.887
InceptionV3	0.945	0.019	0.981	0.901

Table 8: Comparison of the model accuracies

Table 8 shows that the proposed model is better than other models. All the models are run by 30 times to get the average, maximum, and minimum values and standard deviation. The proposed model gives 0.968 accuracy average. The maximum value is 1.0 which means it predicts every class is true. The minimum value is 0.934. The standard deviation is 0.021. ResNet50 gives 0.710 average accuracy, 0.613 minimum and 0.802 maximum accuracy. It's standard deviation is 0.048. VGG19 model gives accuracy 0.937, maximum 0.972 and minimum 0.887 values. The standard deviation of it is 0.018. The last model, InceptionV3, has 0.945 average accuracy, 0.901 minimum accuracy and 0.981 maximum accuracy. Also, it has 0.019 standard deviation. Considering these results, it is clear that the proposed model gives the best average, maximum and minimum values.

It is necessary to compare the values given in Table 8 statistically. Because it should be determined whether the differences are statistically significant, the two-sample t-test can be applied using mean values and standard deviations. Two-sample t-test results are given in Table 9. The p values show the significance of the difference. If p values are below 0.05, it is significant. If it is not below 0.05, it is not significant.

Model	Proposed model	ResNet50	VGG19	InceptionV3
Proposed model	-	<0.001	<0.001	<0.001
ResNet50	<0.001	-	<0.001	<0.001
VGG19	<0.001	<0.001	-	0.099
InceptionV3	<0.001	<0.001	0.099	-

Table 9: Two-sample t-test results for the models (p values)

Table 9 shows that p values between the proposed model and the other models are under 0.05. it means the difference between the proposed model and other models is significant. It can be claimed that the proposed model is better than other models. Also, the statistical test shows there is no significant difference between VGG19 and InceptionV3. The proposed model is the best model, then VGG19 and InceptionV3 are better than ResNet50. The results show that the proposed model can be used for cotton disease detection easily. Farmers and professionals can use it. It is a lightweight model, so it can work on a smartphone or simple device.

5 Conclusion

Cotton has a very important place both in the textile sector and in sub-sectors such as oil. There are countries or regions with high economic income thanks to cotton. Cotton production has a very critical topic for the economy and health. It is very important to detect the diseases that may occur in the cotton plant because undetected errors are transmitted and cause great damage to production. Cotton farmers should control diseases so that they can take precautions with early diagnosis. In this way, they are protected from great harm. Cotton diseases can be detected from leaves. A device can be used for this, or mobile phones can be used. It is necessary to use images for disease detection. Therefore, the CNN model can be used. There are some advanced models for CNN. But these models are general models. Using a customized model for disease detection for cotton diseases can greatly increase success. In this study, a lightweight network structure is tested for this aim. For the architecture of this lightweight network structure, optimization is performed with the GWO algorithm. In this way, this lightweight model has been compared to other classic models and surpasses them. It is both lighter and gives higher accuracy. This is advantageous for an automation system to be installed in the fields or for a system to be used by farmers manually. Considering the statistical tests, the proposed model is statistically significantly more successful than the ResNet50, VGG19, and InceptionV3 models.

In future studies, this method or similar methods can be used for disease detection of different plants. Alternatively, the automatic detection of diseases can be achieved by integrating with different systems. Systems such as robots or cameras can be used. Thus, a more practically useful site conversion occurs. Automation and artificial intelligence would also be used in the field of agriculture and would be beneficial for the future of the world. In addition, new metaheuristic algorithms can be tested for disease detection. It is another research topic. Using artificial intelligence in agriculture has lots of new opportunities.

Data availability statement

The data used in this study is public data and accessible at https://www.kaggle.com/datasets/janmejaybhoi/cotton-disease-dataset.

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