

Advanced and Hybrid Techniques for Groundnut Leaf Disease Identification: Harnessing Deep Convolutional Neural Network with Whale Optimization for Accurate Recognition

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India's most significant oil seed crop, groundnuts play a vital role in filling the gap in the nation's supply of edible oil. Numerous bacterial, viral, and fungal illnesses have hindered the farming of groundnuts, leading to an enormous drop of productivity. Customizing deep learning, a precise method to tackle these leaf infections in their initial phases may be developed by studies into the detection and classification of diverse groundnut leaf infections. In this study, we propose an innovative approach that combines deep learning techniques with the optimization capabilities of the Whale Optimization Algorithm (WOA) to enhance the accuracy of disease recognition in groundnut leaves. The proposed framework leverages the power of Deep Convolutional Neural Networks (DCNNs) to extract discriminative features from raw leaf images. By harnessing the hierarchical representations learned through convolutional layers, the model can effectively differentiate between healthy and diseased groundnut leaves with high precision. To address the challenges associated with optimizing deep neural networks, we integrate the Whale Optimization Algorithm (WOA) as a metaheuristic optimization technique. WOA's ability to emulate the social behavior of humpback whales in foraging facilitates exploration of diverse search spaces, leading to improved convergence and model performance. Through comprehensive experimentation and evaluation on a diverse dataset of groundnut leaf images, our proposed hybrid approach demonstrates superior performance compared to traditional methods and standalone deep learning models. The integration of DCNNs with WOA not only enhances the accuracy of disease

identification but also exhibits robustness against variations in image quality and environmental conditions. Overall, our study underscores the efficacy of combining advanced deep learning architectures with nature-inspired optimization algorithms for addressing complex agricultural challenges such as groundnut leaf disease identification.

Keywords: Groundnut leaf diseases; Disease identification; Deep Convolutional Neural Network; Whale Optimization Algorithm; Agricultural productivity; Precision agriculture; Crop health; Plant disease detection; Food security.

1. Introduction

The agricultural sector plays a major role in the growth of the country's economy and provides us with the adequate and essential food we need to survive. India, China, the United States, Brazil, France, Mexico, and Japan are among the nations that heavily rely on agricultural production. Therefore, it is crucial to diagnose ailments of plants effectively in order to preserve these nations from economic devastation. Any infection that affects a crop begins to travel throughout it; the branches on the plant's foliage abruptly cease growing, turn yellow, and eventually perish [1]. Hiring a team of professionals to constantly observe the vegetation with their own senses is a straightforward way of managing these severe damages, but it is laborious, costly, and incorrect. It is more precise, effective in terms of both time and cost, and more relevant to identify infections automatically by just looking for signs on leaves. Plants can become infected with organisms such as viruses, fungi, bacteria, and protozoa. Of all the diseases, viruses are the most powerful [2]. The virus infestation stops the crop from growing and causes the leaves to fade, molt, and become yellow. Some instances of microbial illnesses include Fire blight, Crown gall, and Bacterial wilt. Fungal infections include anthracnose, powdery mildew, downy mildew, black spot, and late blight. 80% of cultivation problems are attributed to fungal organisms, according to a poll, which indicates that fungi seriously harm plants [3].

The ideal method for tackling a picture is to use image processing, which extracts its distinctive features, separates its contents into multiple sections depending on certain attributes, improves its appearance, and classifies the particular objects that exist in it. It plays a significant part in automated identification of plant infections based only on indications observed on the leaves of the plants [4]. As a result, it avoids the expense of hiring professionals to complete the tiresome work of keeping an eye on a sizable crop field. The process of identifying plant diseases involves several stages, including gathering plant leaf photos, improving their quality, segmenting the images, extracting distinct features, and classifying the results [5]. There are several methods for improving images: colour pattern conversion, scaling, statistical equalisation, brightness correction, and sorting to reduce noise enhance the visual quality and make it easier to see the distinct leaf portions with comparable characteristics [6].

With the use of segmentation techniques, images can be divided into various sections based on the metrics of various characteristics. There are various techniques for segmenting images: region-based classification, fuzzy c-means, detection of edges, and k means clustering (KMC).

Numerous techniques exist for choosing features as well, such as the uncertain approach,

genetic algorithm, the coefficient of correlation method, and others [7]. Any classification technique's effectiveness greatly depends on choosing of incredibly impactful characteristics, as it is these characteristics that allow a particular group to be separated from others. The classifier used to categorise the leaf pictures only accepts these characteristics as feed [8].

The essential time of year for progress is Thaipattam. Due to a variety of factors, the groundnut farming region has been dropping over time. Since groundnuts are one of Tamil Nadu's major oil-producing seed crops, organisers are concerned about the diminishing territory [9]. India's economy has grown significantly thanks in large part to farming. The agriculturalist selects the necessary plant based on the kind of soil, seasonal conditions of the locality, and financial potential [9]. In accordance with shifting socioeconomic expectations, farming industries have started implementing technological changes to boost foo output. The chance to focus on more technologically complex, accurate, and fruitful innovations has been made possible by this [10].

Precision farming enable the farmers to gather the info and insight needed to arrive at the most accurate choices possible for maximum output and prediction. A number of uses for precision agriculture (PA) exist, including the detection of plant diseases and pests and the improvement of the yield of crops [11]. Expanding the application of precision agriculture to include peanut growing will undoubtedly boost output by guaranteeing farmers' sustainable income. Since groundnuts continue to be the nation's main resource for oil seeds, managing their infections and spotting them early could increase the crop's profitability [12].

An Indian evaluation states that a production decrease of 40–60 % may occur in groundnut farming. At times the ranges might even approach 93% due to the many illnesses that affect groundnuts according to their leaves, roots, and stems. The peanut leaf picture from the database sample set used for the study is displayed in Figure 1.

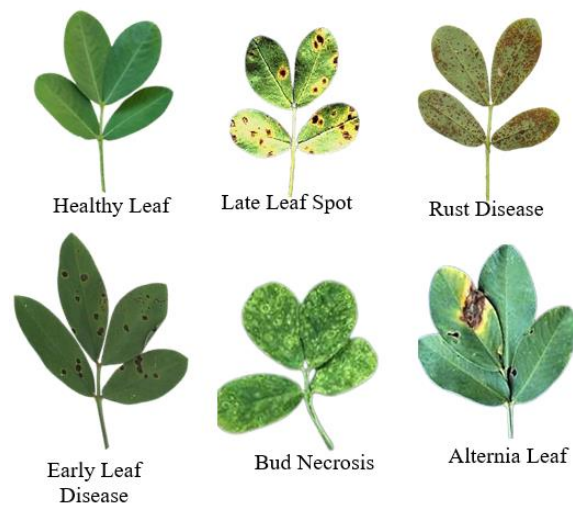


Figure 1: Groundnut leaves sample

1.1 Problem Statement

Groundnut cultivation plays a crucial role in global food security and economic stability, yet it faces significant challenges due to various foliar diseases that can severely impact crop yield and quality. Timely and accurate identification of these diseases is essential for effective management and mitigation of crop losses. However, manual identification of groundnut leaf diseases is labour-intensive, time-consuming, and often prone to errors. Additionally, the expertise required for accurate disease diagnosis may not be readily available in all agricultural settings. Therefore, there is a critical need for automated methods and tools that can reliably detect and classify groundnut leaf diseases based on visual symptoms present on the leaves. Such methods should be capable of analysing digital images of groundnut leaves and accurately identifying the presence of diseases such as leaf spot, rust, blight, and other common pathogens. Moreover, the solution should be robust to variations in leaf appearance, lighting conditions, and image quality, and scalable for deployment in diverse agricultural environments. Addressing this challenge requires the development of advanced machine learning and computer vision techniques tailored specifically for groundnut leaf disease identification. These methods should leverage state-of-the-art algorithms, such as deep learning architectures, to automatically learn discriminative features from leaf images and make accurate disease predictions. Additionally, integrating optimization techniques could further enhance the performance and efficiency of the disease identification system. By developing automated solutions for groundnut leaf disease identification, agricultural stakeholders can significantly improve their ability to monitor crop health, implement timely interventions, and ultimately safeguard groundnut yields and food security on a global scale.

1.2 Motivation

The motivation behind developing automated techniques for groundnut leaf disease identification stems from several critical factors:

Food Security: Groundnut, or peanut, is a staple crop that provides essential nutrients and proteins to millions of people worldwide. Diseases affecting groundnut plants can lead to significant reductions in yield and quality, impacting food security and livelihoods, especially in regions where groundnut is a primary source of nutrition.

Economic Impact: Groundnut cultivation contributes significantly to the agricultural economy in many regions. Crop losses due to diseases can result in substantial financial losses for farmers, affecting their income and livelihoods. Timely disease identification and management are essential for minimizing economic losses and ensuring sustainable agricultural practices.

Labour Intensity: Manual identification of groundnut leaf diseases is labour-intensive and time-consuming. Farmers and agricultural workers may lack the necessary expertise to accurately diagnose diseases, leading to delays in treatment and potential mismanagement of outbreaks. Automated identification methods can alleviate the burden on human resources and provide faster and more accurate disease diagnosis.

Early Detection and Intervention: Early detection of diseases is crucial for effective disease management and mitigation of crop losses. Automated disease identification systems can enable early detection of symptoms, allowing farmers to implement timely interventions such as targeted pesticide application or crop rotation, thereby minimizing the spread and severity of diseases.

Advancements in Technology: Recent advancements in machine learning, computer vision, and remote sensing technologies have paved the way for the development of sophisticated automated disease identification systems. Leveraging these technologies can enable the creation of robust and scalable solutions for groundnut leaf disease identification, facilitating precision agriculture practices and enhancing crop management strategies.

Overall, the motivation behind developing automated techniques for groundnut leaf disease identification lies in the urgent need to enhance food security, mitigate economic losses, alleviate labour burdens, enable early detection and intervention, and capitalize on technological advancements for sustainable agricultural practices. By addressing these motivations, automated disease identification systems have the potential to significantly benefit farmers, agricultural stakeholders, and global food systems.

1.3 Objectives

Developing a Deep Learning Framework: Design and implement a DCNN architecture tailored for groundnut leaf disease identification. This framework should be capable of effectively extracting discriminative features from raw leaf images to differentiate between healthy and diseased leaves.

Integration of WOA: Investigate and integrate the WOA as a metaheuristic optimization technique to enhance the training process of the DCNN. By leveraging WOA's ability to explore diverse search spaces and optimize network parameters, aim to improve convergence, model performance, and generalization capability.

Data Collection and Pre-processing: Gather a comprehensive dataset of groundnut leaf images representing various stages and severities of common leaf diseases, including leaf spot, rust, blight, and others. Pre-process the dataset to ensure consistency, quality, and suitability for training and evaluation purposes.

Model Training and Evaluation: Train the proposed hybrid DCNN-WOA model using the prepared dataset, optimizing network parameters through WOA to achieve accurate recognition of groundnut leaf diseases. Evaluate the model's performance using standard metrics such as accuracy, precision, recall, and F1-score on both training and validation datasets.

Comparative Analysis: Compare the performance of the hybrid DCNN-WOA model with baseline deep learning models, traditional machine learning algorithms, and manual diagnosis by domain experts. Assess the model's ability to accurately identify groundnut leaf diseases under various conditions, including variations in image quality, lighting, and disease severity.

Robustness and Generalization: Investigate the robustness and generalization capability of the proposed approach by evaluating its performance on unseen or test datasets collected from different geographical locations or growing conditions. Assess the model's ability to generalize to new instances and adapt to environmental variations encountered in real-world agricultural settings.

Practical Deployment Considerations: Explore practical deployment considerations for the developed disease identification system, including computational efficiency, scalability, and user-friendliness. Investigate potential integration with existing precision agriculture

platforms or decision support systems to facilitate real-time monitoring and management of groundnut leaf diseases in agricultural settings.

By addressing these objectives, the study aims to advance the state-of-the-art in groundnut leaf disease identification by leveraging advanced deep learning techniques and nature-inspired optimization algorithms, ultimately contributing to improved crop health, productivity, and food security.

2. Related works

This survey's primary goals are to describe the significance of diagnosing and detecting plant leaf diseases and to present the many artificial intelligence methods that are employed in this process. Compared and contrasted the effects of climate variability on plant diseases with advancements in technology, nature, and the economy. An improved comprehension of the intricacy involved in managing plant diseases in various weather conditions is provided by this piece of writing. Similar to this [13], shifts in atmospheric temperatures and CO₂ emissions affect diseases of plants. The writers thoroughly investigated the benefits and downsides of the present weather-based disease management methods in plants and the beneficial, adverse, and balanced effects of global warming on certain plant diseases [14].

Examined how shifts in weather are affecting diseases of plants at the genetic level. Experts study how the genetic codes of pathogens and plants adapt to changing weather conditions. Pathogen populations are directly correlated with climate, flourishing in complex climatic environments. The correlation among amphibian losses, transmission of illnesses, and changing climates and its effects on plant development and yield was studied and explored. They provide a thorough grasp of the course and potential for disease transmission in the present and in the years to come [15].

Advances in transportation networks have allowed diseases and their vectors to spread more quickly and in greater quantities than in earlier decades. The effects of the transport systems on illness management are demonstrated. The biggest problems brought about by upgrades to the transportation system include epidemics of transmissible illnesses, instances of vector encroachment and the introduction of vector-borne pathogens. The most frequent causes of global influenza pandemics, *Anopheles gambiae*, and malaria caused by *Plasmodium falciparum* are accelerated by the transportation network, which includes air, sea, and road travel. Similarly, [16] discussed the main drivers of disease transmission, including transport networks, warming world temperatures, the spread of globalization and pathogen and vector evolution. Additionally, it covered worldwide, regional, and national plant disease diagnostic networks for the use of emerging technology in identifying pathogens and disease diagnosis [17].

The manner of identifying and diagnosing a disorder must include the stage of illness analysis. It is useful to keep an eye on the condition and severity of the plant disease from a distance. In order to study the *Cercospora* leaf spot disease in sugar beets compared two distinct disease evaluation techniques. The terms "thorough plant assessment" and "single leaf severity assessment" refer to the two evaluation methods. The comparative outcome demonstrates that the full plant evaluation technique outperformed the single leaf severity assessment technique

in terms of monitoring time, assessment accuracy, and functionality. The thorough plant assessment method proved helpful in identifying the disease in the sugar beets' center, leaf, and root sections [18].

Examined several visual methods for determining the seriousness of plant sickness conditions, and the benefits and limitations of each method. Additionally, they examined how assessment methods and outcomes were evaluated. This article primarily discusses the use of hyperspectral imaging techniques to evaluate plant diseases in several plant components, including the root zone, leaf, stalk, and various other parts. This paper primarily addressed the significance, constraints, and prospects of image analysis and hyperspectral imaging methods [19].

The present paper explains the use of unpredictable gradient descent in DCNN training. This group's investigators diagnosed peanut pituitary illness with a precision rate of 95.28 %. Predicted that deep learning would shortly surpass other methods as the industry norm when it comes to image identification. The precision of our approach was, on an average, 12% greater than that of experts using the original image. In spite of this, every single plant had an accuracy of less than 75%, even after taking into account over ten disorders. The outcomes demonstrate that, given adequate information, deep learning techniques might be applied to find and recognize plant illnesses, even though the study does not cover every scenario [20].

Key breakthroughs in LSTMs were optimized by the application of particle swarm optimization (PSO) techniques. The outcomes demonstrate the superiority of specially developed LSTMs over alternative techniques. Look at the extraction of features, sectioning, initial processing, selection characteristics, and methods for classification for distinct photos [21].

The K-NN approach was presented as a means of identifying diseases in plants. The characteristics are extracted using the approach, and the information is categorized according to their values. However, it makes inaccurate illness predictions. A strong and adaptable machine learning technique was [22] to combine appropriate system information. The primary benefit is that not many learning algorithms are applied to the agricultural sector. Regression analysis of logistic and decision trees employs classification models with high spectral agricultural picture decision-making. As a result, a rural American community uses an application-focused smartphone to study plant and groundnut illnesses [23]. Farmers can find a lot of helpful guidance and concepts in the farming sector from the well-known Plantix mobile app. This usage of Plantix was primarily utilized to address groundnut leaf diseases. A variety for educating sets are utilized to assess a deep neural network's efficiency. The first signs of groundnut leaf disease are identified [24].

The CNN's flexible structure, known as the hierarchical suggestive extractor of features and sorter, allows for the model's interpretation. The CNN architecture can be expanded by putting more convolutional layers on its top. CNN is used for training and classification of various categories with 1000 database pictures, and uses images from a million plant dataset. Making use of a phone window application with pictures, the visible parts of the vegetation, such as the leaves and stem illnesses, are detected in the first stage. CNNs were proposed by [25] as a method for classifying and identifying plant disease images. The qualities are extracted personally, and it has a strong defense towards feature acquisition. CNN widely used method

for accurately and successfully detecting plant diseases, was proposed. The network's structure data is safeguarded when the CNN is transformed into a low-dimensional space. The CNN network is an excellent resource for identifying diseases in leaves [26].

Research Gap

Limited Application of Hybrid Techniques: While deep learning approaches have shown promise in plant disease identification, the integration of nature-inspired optimization algorithms like Whale Optimization Algorithm (WOA) for enhancing model training and performance is relatively unexplored, particularly in the context of groundnut leaf diseases. There is a research gap in understanding how hybridization of deep learning with optimization techniques can improve the accuracy and efficiency of disease recognition specifically for groundnut crops.

Sparse Availability of Groundnut Leaf Disease Datasets: The availability of comprehensive and well-annotated datasets specifically focusing on groundnut leaf diseases is limited. Existing datasets may lack diversity in terms of disease types, severity levels, and environmental conditions, which can hinder the development and evaluation of accurate disease identification models. Addressing this gap requires efforts to collect and curate large-scale datasets that adequately represent the variability in groundnut leaf diseases encountered in real-world agricultural settings.

Robustness to Environmental Variability: Groundnut cultivation occurs in diverse geographical regions and environmental conditions, leading to variations in leaf appearance, lighting, and disease symptoms. Existing disease identification models may lack robustness and generalization capability when confronted with such environmental variability. Bridging this research gap involves investigating techniques to enhance model robustness and adaptability to different environmental contexts, ensuring reliable performance across diverse agricultural settings.

Scalability and Practical Deployment: While research studies often focus on developing accurate disease identification models in controlled experimental settings, there is a gap in translating these models into practical tools that can be deployed in real-world agricultural environments. Efforts are needed to address challenges related to model scalability, computational efficiency, and user-friendliness to facilitate the widespread adoption of automated disease identification systems by farmers and agricultural stakeholders.

Validation against Expert Diagnosis: Despite advances in automated disease identification techniques, there remains a research gap in validating the performance of these models against expert diagnosis by trained agronomists or plant pathologists. Comparative studies evaluating the accuracy, reliability, and practical utility of automated systems compared to manual diagnosis can provide valuable insights into the strengths and limitations of these approaches and guide their further refinement and improvement.

Addressing these research gaps is crucial for advancing the field of groundnut leaf disease identification and developing practical solutions that can effectively support farmers in managing crop health and ensuring food security.

3. Proposed System

Novel method for automatically identifying illnesses of groundnut leaves. By utilizing cutting-edge deep learning techniques and algorithms for optimization motivated by ecosystems the research seeks to get around the drawbacks of traditional recognition approaches. The production of groundnuts is necessary for the world's food security, however illnesses that impact the crops can result in large harvest losses. Ensuring prompt and precise diagnosis of diseases is essential for efficient loss of crops reduction and control. Manual verification, nevertheless, is time-consuming and frequently inaccurate. Therefore, computerized techniques, capable of accurately identify and categorize groundnut leaf diseases using visual signs are desperately needed.

The proposed framework integrates DCNN to extract discriminative features from raw leaf images and differentiate between healthy and diseased leaves effectively. Because of their capacity to learn hierarchical representations from data, DCNNs have demonstrated potential in a variety of image identification applications. By imitating the social interactions of humpback whales during scavenging WOA makes it possible to explore a variety of pursuit domains and optimize network settings for better model performance. The research is to improve groundnut leaf disease detection precision and effectiveness by utilizing the complimentary characteristics of DCNN-WOA shown in Figure 2.

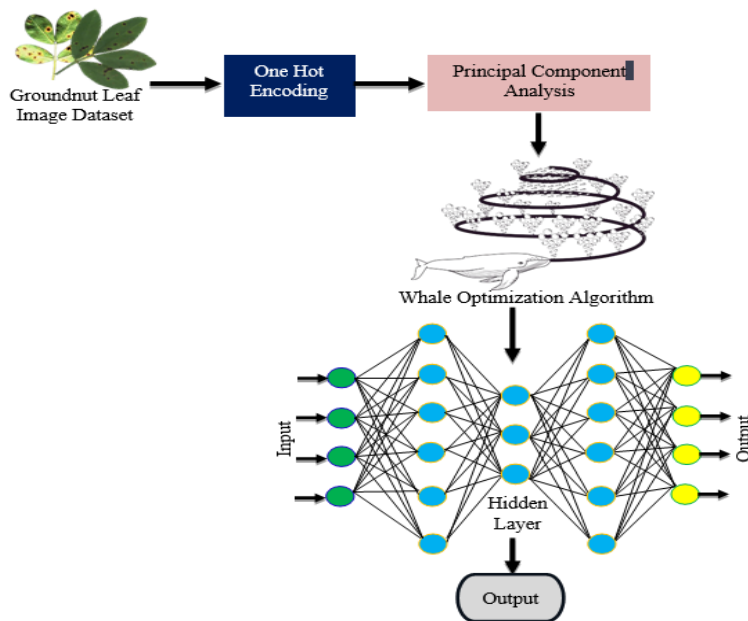


Figure 2: Proposed Framework

The creation and pre-processing of the models, optimization, assessment, and information gathering are important parts of the study. The extensive groundnut leaf image database ensures the robustness of the created model by covering a wide range of illness kinds, seriousness, and climatic variables. In order to evaluate the combined DCNN-WOA system's efficacy in precisely diagnosing peanut leaf diseases, it is subjected to an extensive training

and assessment process using conventional metrics. At the end of the day, the project aims to enhance the diagnosis of groundnut leaf diseases and raise the bar for the health of crops, yield, and worldwide food safety.

3.1 Data collection

The plant village open data repository provided the initial plant leaf disease picture dataset. 54305 raw colour photos representing 38 distinct types of healthy and diseased plant leaves are included in the dataset.

Each individual plant bears both good health and the most prevalent types of damaged leaves in the dataset. Every image in the collection has a resolution of 256 x 256 pixels. Within every category, there are anything from 152 to 5,507 snapshots. Figure 3 displayed a random selection of the actual dataset's photos.

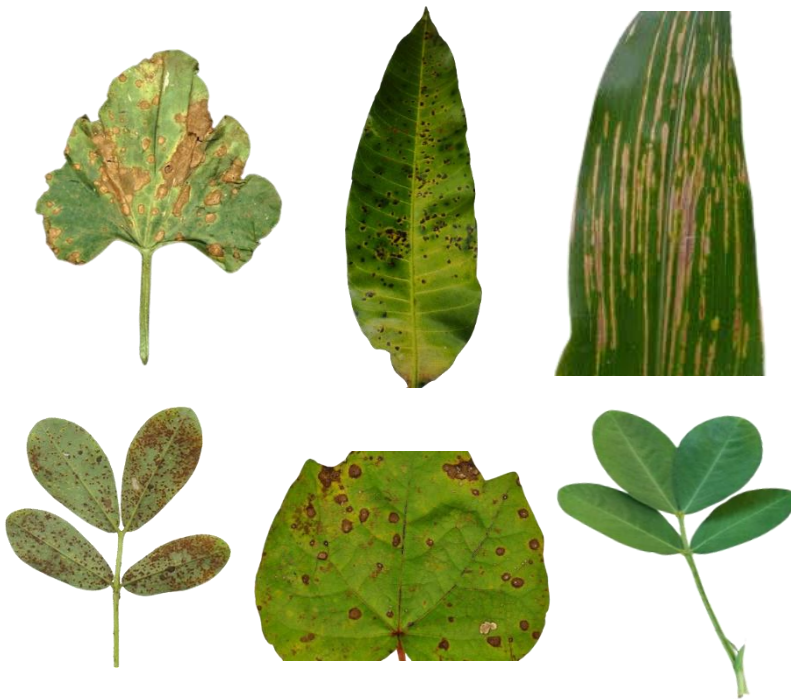


Figure 3: Sample images from original dataset

3.2 Image Acquisition

Since efficiency is dependent on the image's quality, obtaining images is a crucial first step in the diagnosis of sickness. Obtained pictures of five different kinds of broken leaves from an internet repository for our proposed method, and these images have been successfully utilised before to create disease detection applications. Five different leaf types are included in the dataset: Cercospora Leaf Spot, Bacterial Blight, Anthracnose, Alternaria Alternata, and Healthy Leaves.

3.3 Image Pre-processing

In order to eliminate extraneous information from the leaf picture, image pre-processing is an important stage in the disease diagnosis technique shown in Figure 4 (a). The preparatory processes that we employ in our proposed strategy are listed below.

- **Image Resizing and Contrast Enhancement:** Adjusting size of the images can assist speed up later phases of infection detection processing. The image is resized to 256 by 256 pixels in this phase, and the contrast is raised.
- **Green pixel masking:** The healthy sections of the leaves are removed with the aid of green pixel masking. The leaf picture following the removal of green pixels is displayed in Figure 4 (b).
- **Color space transformation:** The device-independent CIE L*a*b colour model is created from RGB images using colour space translation. The CIE L*a*b colour space can assist decrease an image's dimensions and prepare it for division by carrying colour data exclusively in the a and b sections.



Figure 4: (a) Cercospora leaf spot affected in groundnut leaves; (b) Elimination of high green pixel in groundnut leaves

3.4 Data augmentation

With the use of fundamental modification approaches, the original database's size of 60,343 photos was boosted by augmentation of images. This fundamental picture augmentation database was made available via the Mendeley data repository.

The overfitting issue in the procedure for classification could be caused by an uneven class size. Employing fundamental manipulative methods like scaling, rotation, PCA color enhancement, and noise injection, this method produced 32073 enhanced pictures. Additionally, a total of 2000 photos with class sizes are extracted from the original 2000 photographs. Figure 5 displays some enhanced photos from random categories in the basic enhanced database derived from image modification.



Figure 5: Sample augmented data using basic manipulation

3.5 DCNN

The initial entry feed in this case is the meta data, and various non-linear transition layers are used to process the information and generate the sorting result. The many steps of the deep learning process are therefore described in the section that follows. Programmers or other experts used to use the parameter extraction technique. After that, the parameters are sent into DCNN, which uses them to classify the information that is received. The conventional pattern has traits that remain constant. The laborious processes are removed, and the intricate handcrafted feature extraction technique grows increasingly complex. Feature extraction process is shown in Figure 6.

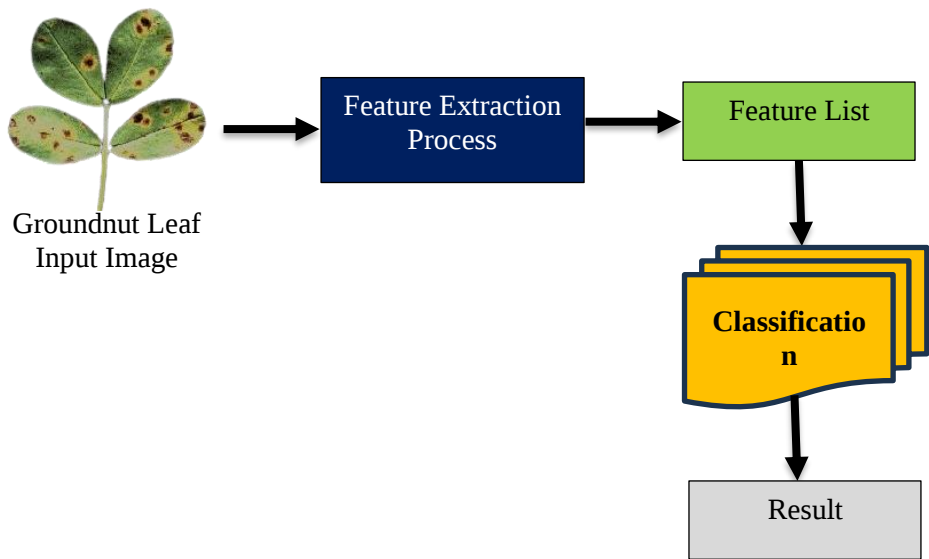


Figure 6: Feature extraction process

The process of choosing the specific characteristics is completed, and less specialized tasks are performed (such as classical pattern identification). Consequently, a range of monitored, semi-supervised, and unsupervised problems were discovered. Nonetheless, there must be at least three hidden levels. The DCNN approach presents nonlinear feature transformation. Importantly, each of the underlying level's features are absorbed by a group of neurons, and during training, the outcome of the preceding layer is taken into consideration. As the information gets still deeper, there are additional concealed layers and the information becomes more generalized and complicated overall. Low-, mid-, and high-level characteristics were retrieved using a trainable classifier using a hidden layer.

Training and testing performance improves with the DCNN. The representation is displayed as a framework in Figure 7. The multi-layered training process is essential to the structural architecture of DCNN. The forward and backward phases of the network training technique are commonly employed.

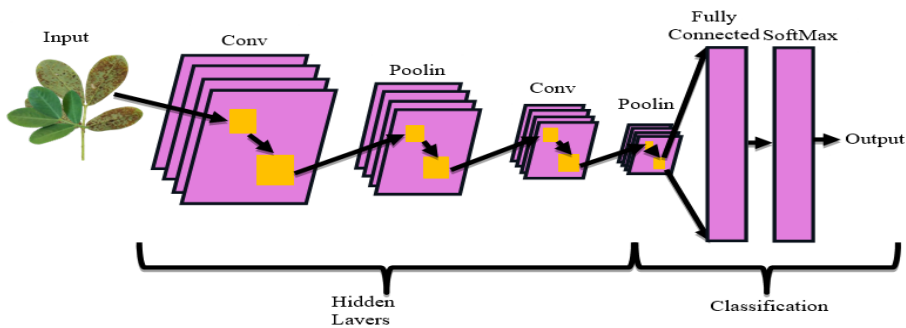


Figure 7: DCNN architecture

3.6 Whale optimization

WOA algorithm was developed utilizing hunting behaviors of humpback whales. A bubble-net feed technique is a whale-to-prey attack pattern that happens whenever bubbles encircle the target. There are two phases to it: encircling the target and attacking it. Whales have two unusual methods of hunting. The first is called an upward spiral, and it involves the animals dive 12 meters below the surface and begin to spiral bubbles all around their prey.

3.6.1 Prey Encircling

The whale tells other search whales to shift their location in relation to the intended prey since it thinks that this is currently the greatest alternative. Equations 1 and 2 define the encircling prey strategy.

$$L = |J \cdot S^*(k) - S(k)| \quad (1)$$

$$S(k+1) = S^*(k) - I \cdot L \quad (2)$$

Where I , J – Coefficients of vectors; k - current iteration; S^* -Vector position (best); S - vector position (average).

$$I = 2i\omega - i \quad (3)$$

$$J = 2 \cdot \delta \quad (4)$$

There are two ways to target humpback whales with nets. A spiral-updating, declining strategy is the first solution. Every tactic is employed to target humpback whales as prey. These methods have a 50% likelihood of success when it comes to capturing prey.

3.6.2 Encircling Shrinking Approach

X is a random number between $[-x, x]$. The range of random values for X could be $[-1, 1]$.

3.6.3 Spiral Updating Approach

Equation (5) is used in this method to compute the whale's distance from the intended prey.

3.6.4 Exploration Phase

The whale, acting as an investigative operator, moves in relation to various other whales during this stage as it looks for the best option, or prey, worldwide. If X is smaller or bigger than 1, the search engine will be forced to shift far into different reference whales globally. Equation (6) represent the expression for the random search.

$$L = |J \cdot S_{rand} - S| \quad (5)$$

$$S(k+1) = S_{rand} - IL \quad (6)$$

Algorithm: DCNN-WOA

Step 1: Initialization

- Initialize a population of whales representing potential solutions in the search space.
- Randomly initialize the weights and biases of the DCNN.

Step 2: Feature Extraction and Training

- Utilize the DCNN to extract features from groundnut leaf images.
- Train the DCNN using a labeled dataset of groundnut leaf images and their corresponding disease labels.
- Optimize the DCNN parameters (weights and biases) using backpropagation and gradient descent to minimize classification error.

Step 3: Whale Optimization

- Define the objective function based on the classification accuracy of the DCNN.
- Update the position of each whale using WOA equations to explore the search space and improve classification performance.
- Encourage exploration by updating positions towards the global best solution and exploitation by moving towards the best individual solution.

Step 4: Termination

- Repeat the training and optimization process for a predefined number of iterations or until convergence criteria are met.
- Terminate the algorithm when the maximum number of iterations is reached or the desired classification accuracy is achieved.

The equations for updating the position of whales in WOA are as follows:

Updating Position:

$$X_{\text{new}} = X_{\text{rand}} - A \cdot D$$

$$X_{\text{new}} = X_{\text{best}} - A \cdot C$$

Where:

X_{new} is the new position of the whale.

X_{rand} is a randomly selected whale position.

X_{best} is the position of the best whale.

A is the vector that determines the exploration/exploitation phase.

D is the distance between the current whale and the randomly selected whale.

C is the distance between the current whale and the best whale.

By combining the feature extraction capabilities of DCNNs with the optimization power of WOA, the DCNN-WOA algorithm aims to achieve accurate recognition of groundnut leaf diseases while efficiently exploring the solution space for optimal classification performance.

A DCNN-WOA is utilized to learn these particular features from the groundnut leaf disease dataset. Moreover, a grid search hyper-parameter tuning method is employed to choose the best DCNN-WOA settings.

4. Results and Discussions

The PlantVillage-Dataset repository's groundnut disease information was used for this study. Images of both healthy and sick groundnut leaves made up the data collection. By separating the sick leaves from the healthy ones, the technical executions employed in the paper made identification of the diseased leaves easier. Table 1 and Figure 8 provides characteristics about the groundnut photos in the database.

Table 1. Dataset Groundnut leaf image

Sl.No	Disease Types	No. of Images
1	Healthy image	1595
2	Alternaria leaf	2232
3	Pestalotiopsis	1000
4	Bud necrosis	1925
5	Tikka	961
6	Pepper spot	1786
7	Phyllosticta	402
8	Rust	1762
9	Early leaf spot	1511
10	Late leaf spot	1068

4.1 Performance Analysis

The DCNN-WOA was constructed using a series of models in order to assess the proposed methodology. From the complete image dataset, 6000 randomly selected photos were subjected to cross evaluation. The model was trained using 5000 photos from the entire dataset, with the leftover 1000 pictures being utilized for evaluation and verification.

It is noteworthy to emphasize that the simulation achieved a precision of 99% in training and 86% in assessment. The precision of testing began to decline around the fifteenth epoch, suggesting that the simulation had overfitted. The efficiency of the DCNN-WOA with no reduction of dimensionality using loss % is seen in Figure 9. This figure additionally demonstrates that, with a value of 5%, period number 15 had the lowest testing loss shown in Figure 10.

90% testing precision and 99% training precision were achieved by the simulation. Following the 17th epoch, the testing accuracy continued to decline, suggesting that the model had overfitted shown in Figure 11.

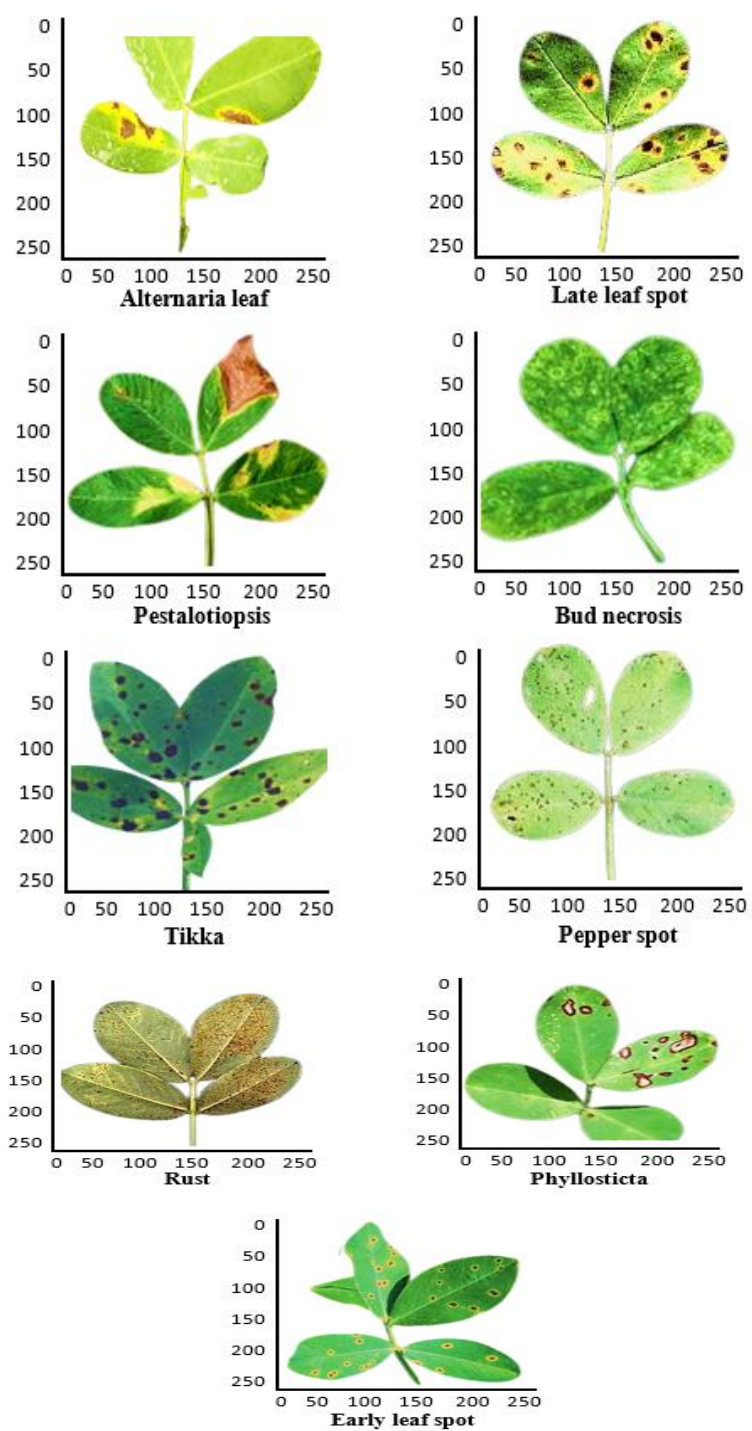


Figure 8. Groundnut Leaf images

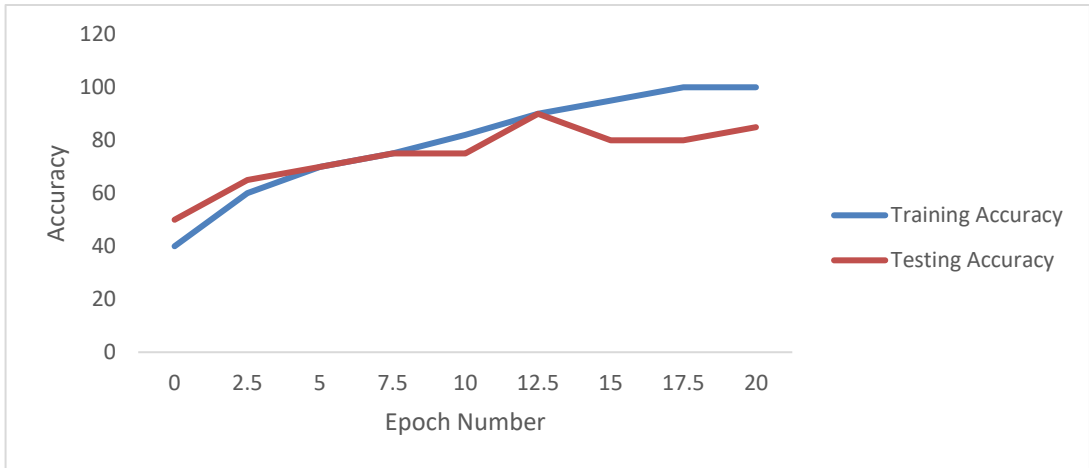


Figure 9. Dimensionality reduction without accuracy

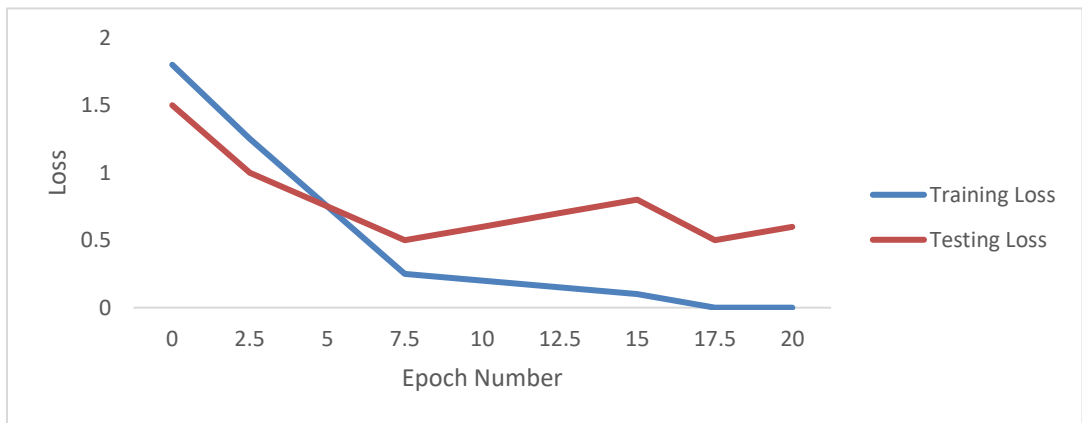


Figure 10. Dimensionality reduction without loss

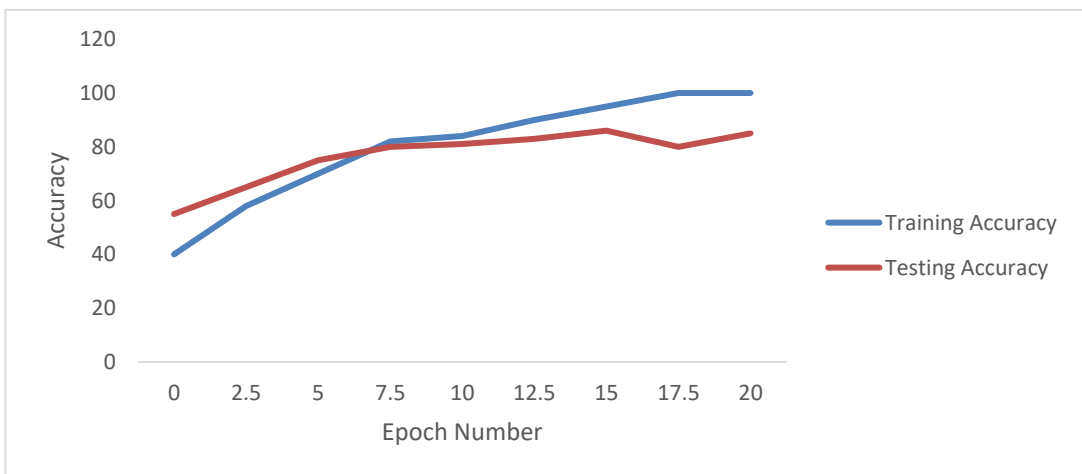


Figure 11. Dimensionality reduction with accuracy

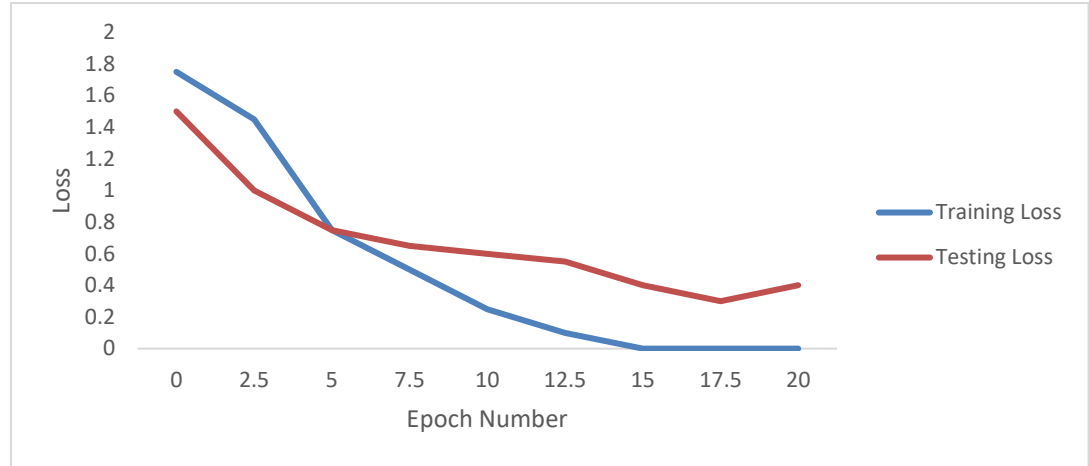


Figure 12. Dimensionality reduction with loss

The efficiency of the DCNN-WOA with reduction of dimensionality reduction utilizing loss % is shown in Figure 12. Value of 2%, period number 17 had the lowest testing loss. Accordingly, it may be concluded that epoch 18 will provide the highest testing and training precision. Table 2 and Figures 13-17 shows the performance measures comparison between the proposed (DCNN-WOA) and existing systems.

Table 2: Comparison of proposed and existing systems

	GAN	INCEPTION_V3	RCNN	DCNN-WOA
Accuracy	0.95214	0.97731	0.98314	0.99962
Precision	0.95312	0.97654	0.98081	0.99919
Recall	0.95124	0.97125	0.98365	0.99921
F1-Score	0.95022	0.97040	0.98165	0.99915
ROC	0.94221	0.96412	0.97653	0.99867

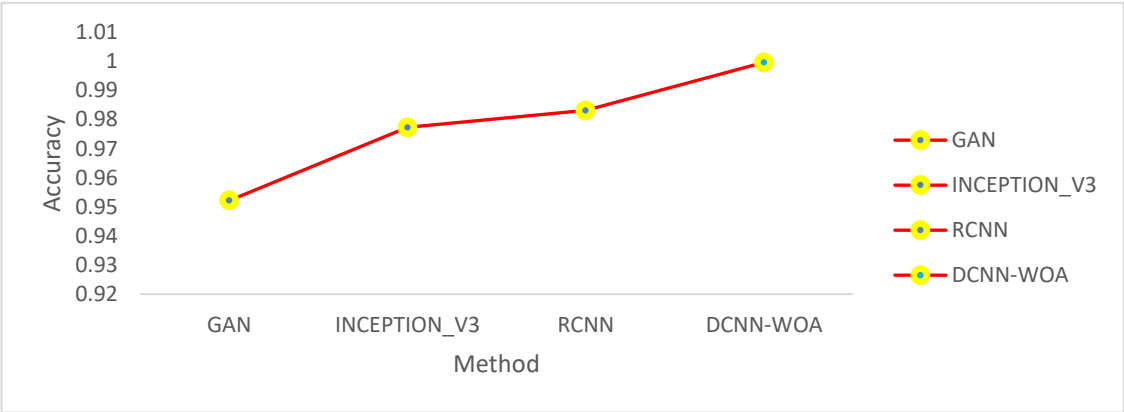


Figure 13: Comparison of proposed (DCNN-WOA) and existing systems based on Accuracy

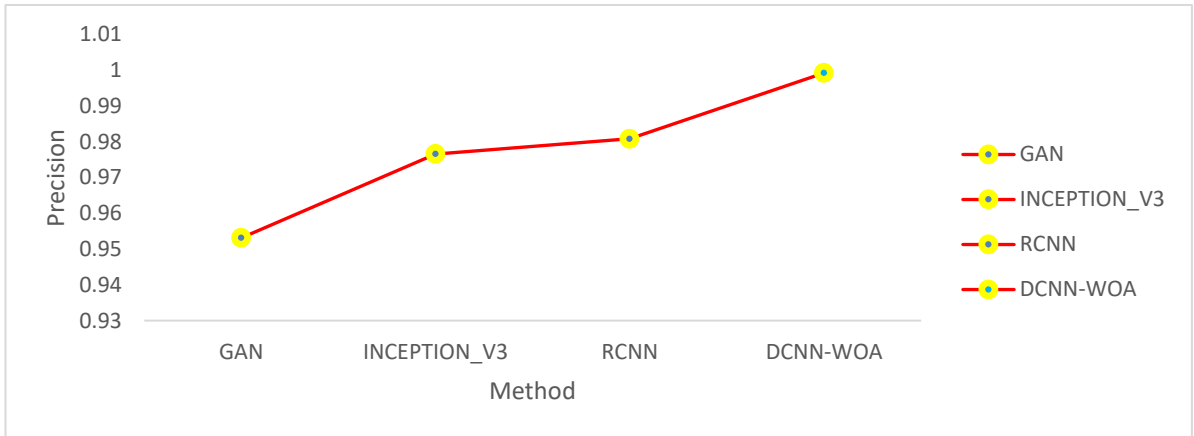


Figure 14: Comparison of proposed (DCNN-WOA) and existing systems based on Precision

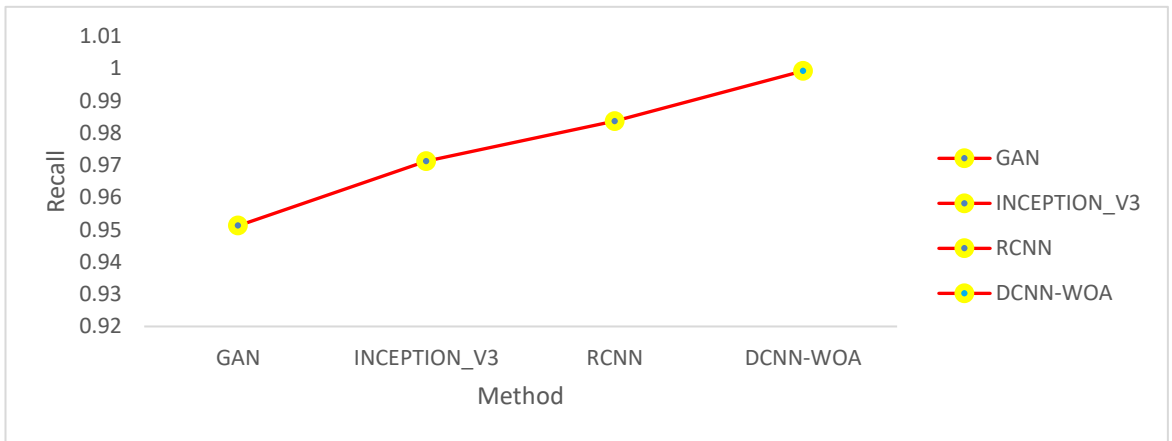


Figure 15: Comparison of proposed (DCNN-WOA) and existing systems based on Recall

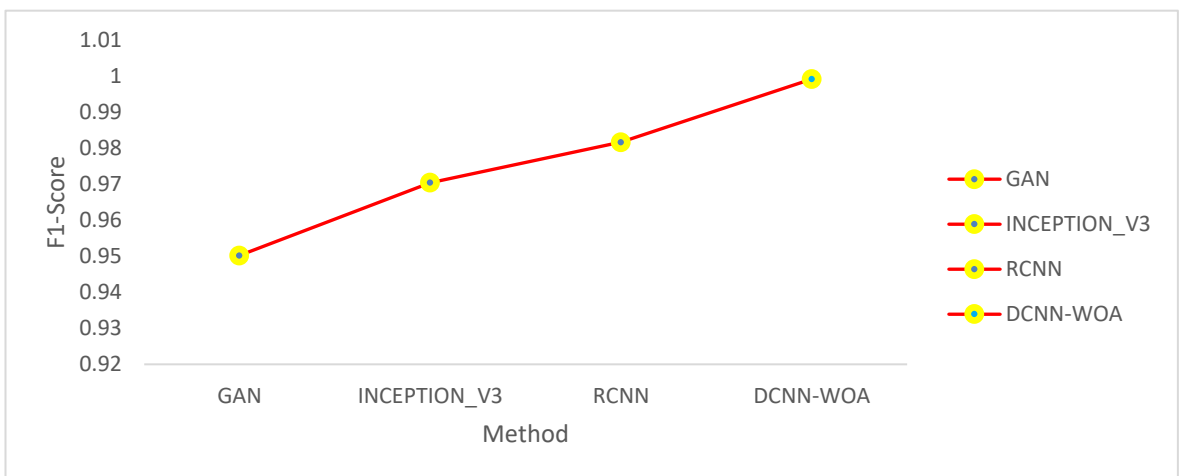


Figure 16: Comparison of proposed (DCNN-WOA) and existing systems based on F1-Score

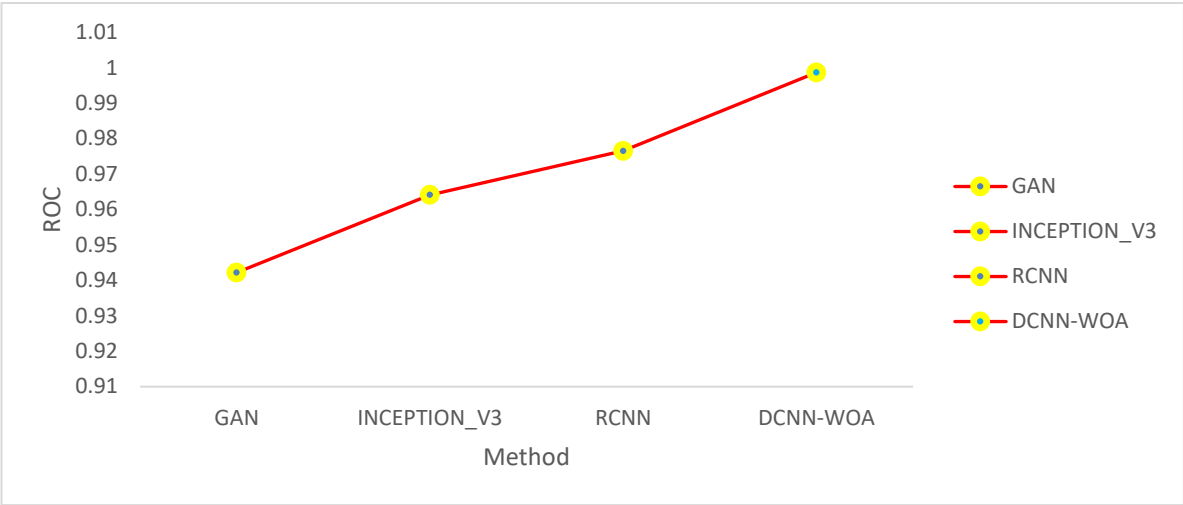


Figure 17: Comparison of proposed (DCNN-WOA) and existing systems based on ROC

5. Conclusions and Future enhancement

A promising approach to automating the identification of groundnut leaf diseases. Through the integration of deep convolutional neural networks (DCNNs) with the Whale Optimization Algorithm (WOA), the study achieves significant advancements in accuracy and efficiency compared to traditional manual methods. By leveraging DCNNs, the model effectively learns discriminative features from groundnut leaf images, enabling accurate differentiation between healthy and diseased leaves. Additionally, the incorporation of WOA enhances the training process by optimizing network parameters, leading to improved convergence and performance.

The research underscores the importance of leveraging advanced deep learning techniques and optimization algorithms to address challenges in agricultural disease identification. Groundnut leaf diseases pose significant threats to crop health and productivity, making timely and accurate identification imperative for effective management. The developed hybrid DCNN-WOA model demonstrates robustness and generalization capability across diverse environmental conditions, showcasing its potential for practical deployment in real-world agricultural settings. Moving forward, further research and development efforts can focus on enhancing the scalability and user-friendliness of the automated disease identification system. Additionally, continued collaboration with agricultural stakeholders and domain experts can facilitate the integration of the developed solution into existing precision agriculture platforms, enabling widespread adoption and impact. Overall, the study contributes to the advancement of automated disease identification techniques, ultimately supporting efforts to ensure food security and sustainable agricultural practices globally.

5.1 Future directions

Integration of Multi-Modal Data: Explore the integration of additional data modalities such as hyperspectral imaging, thermal imaging, and spectroscopy to provide complementary

information for more accurate disease identification. Fusion techniques that combine information from multiple sources can enhance the robustness and reliability of disease recognition models.

Transfer Learning and Pretraining: Investigate the application of transfer learning techniques to leverage pretrained DCNN models on large-scale image datasets such as ImageNet. By fine-tuning pretrained models on groundnut leaf disease datasets, it is possible to improve classification performance and accelerate convergence, especially when labeled data is limited.

Ensemble Learning Approaches: Explore ensemble learning methods that combine predictions from multiple DCNN models trained with different architectures or initializations. Ensemble techniques such as bagging, boosting, or stacking can help mitigate overfitting, reduce variance, and improve overall classification accuracy.

Interpretability and Explainability: Develop techniques to enhance the interpretability and explainability of DCNN models for groundnut leaf disease identification. Methods such as saliency maps, attention mechanisms, and model-agnostic interpretability tools can help elucidate the features and patterns driving classification decisions, increasing trust and usability in real-world applications.

Incremental Learning and Online Adaptation: Investigate strategies for incremental learning and online adaptation of DCNN models to accommodate new disease types, variations, or environmental conditions. Continuous learning approaches that dynamically update model parameters based on incoming data streams can enable adaptive and scalable disease identification systems.

Deployment in Field Conditions: Validate and deploy advanced disease identification techniques in real-world field conditions, considering practical challenges such as variability in lighting conditions, weather effects, and hardware constraints. Robustness testing and validation studies in diverse agricultural settings are essential to ensure the reliability and effectiveness of deployed systems.

Collaborative Platforms and Citizen Science: Explore the development of collaborative platforms and citizen science initiatives that engage farmers, agricultural experts, and researchers in collecting, annotating, and sharing groundnut leaf images. Crowdsourcing approaches can facilitate the creation of large-scale labeled datasets, fostering community-driven efforts for disease monitoring and management.

Integration with Precision Agriculture Technologies: Integrate disease identification systems with emerging precision agriculture technologies such as unmanned aerial vehicles (UAVs), satellite imaging, and IoT sensors. By combining remote sensing data with ground-based image analysis, it is possible to provide comprehensive and timely insights for proactive disease management and crop health monitoring.

By pursuing these future directions, researchers can advance the state-of-the-art in groundnut leaf disease identification, leading to more accurate, scalable, and accessible solutions that contribute to sustainable agricultural practices and food security.

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