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Automated Detection of Groundnut Plant Leaf Diseases using Convolutional Neural Networks

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ABSTRACT

Background: Groundnuts, commonly known as peanuts, are a significant legume cultivated globally, with China and India being the leading producers. Groundnut production faces challenges from pests, diseases and climate change, impacting yield and quality. In addition to notable diseases like rust, early and late leaf spots, plant health is also impacted by nutritional deficiencies. Sustainable production requires the management of diseases and the supply of appropriate nourishment.

Methods: This study applies machine learning (ML), specifically Convolutional Neural Networks (CNNs), to detect groundnut disease symptoms. A CNN-based tool is developed to assess disease severity efficiently. The model is trained and validated using a dataset of 3,058 groundnut leaf images, classified into five disease categories.

Result: After 100 epochs, the CNN model reached a training accuracy of 91.94% and a validation accuracy of 90.97%. Performance metrics such as precision, recall and F1-score confirm the model's effectiveness in disease classification. The study acknowledges certain limitations, including a small dataset and a focus only on leaf infections. Future work may expand the dataset, include other plant parts and compare various ML approaches.

Key words: CNN, Disease classification, Groundnut, Leaf diseases, Machine learning, Training, Validation accuracy.

INTRODUCTION

Groundnuts, also commonly known as peanuts, are a type of legume that belongs to the Fabaceae family. This plant species is widely cultivated in various parts of the world. China and India are the lead producers, as per the Food and Agriculture Organisation of the United Nations (Fig 1). The top ten producers account for more than 70% of world production. Groundnut is a vital subsistence food crop in tropical regions, cultivated mainly for kernels used in edible oil, meal and vegetative residue. The kernels contain 47-53% oil, 25-36% protein and 10-15% carbohydrates. They also include phosphorus and are a good source of vitamins B and E (Prasad *et al.,* 2010).

They are also a valuable cash crop for farmers in developing countries. Several factors, such as population growth, rising incomes and the growing use of groundnut oil in biofuels, contribute to the increasing demand for groundnuts (Raman, 2022; Sinare *et al.,* 2021).

The production of groundnuts is facing several challenges, including pests, diseases and climate change (Fig 2). These challenges are likely to become more severe in the future, making it important to develop new technologies and practices to improve groundnut production (McDonald *et al.,* 1985; Pal *et al.,* 2014; Singh *et al.,* 2004).

Plants are complex organisms where different parts are connected and influence each other's health. A disease affecting the leaves may also spread to other parts of the plant. That will impact plants' growth and productivity. Moreover, plants interact with other organisms, such as insects, fungi and bacteria and play important roles in their health. Thus, a computational approach that can consider the entire plant system is necessary for effective disease management. Addressing leaf diseases alone may provide temporary relief but might not address the root causes of plant health problems. Many plant diseases have underlying factors such as soil health, environmental conditions, or cultural practices that contribute to their development. Neglecting these factors can result in recurrent outbreaks of diseases despite efforts to control them.

There are several diseases related to roots, pods and stems that harm peanut plants and can significantly impact crop yield and quality. Here are some common diseases that affect the roots and stems of groundnuts.

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Root rot

Root rot is a fungal disease that is caused by pathogens such as *Rhizoctonia solani*, *Fusarium* spp. and *Sclerotium rolfsii*. These pathogens infect the roots of groundnuts, leading to rotting and decay. Symptoms include wilting, yellowing and necrosis of lower leaves, stunted growth and eventually plant death. Infected roots may appear darkened, water-soaked and mushy. Root rot can be grew by excessive soil moisture and poor drainage.

Stem rot

Stem rot, also known as collar rot or white mold, is primarily caused by the fungus Sclerotinia sclerotiorum. This disease affects the stems and lower branches of groundnut plants, causing soft, water-soaked lesions that eventually become covered in white fungal growth. As the disease progresses, the stems may become girdled, leading to wilting and death of the plant above the infection point. Stem rot thrives in cool, moist conditions and can spread rapidly under high humidity.

Pod rot

Pod rot is another fungal disease that affects the pods and stems of groundnuts. It is caused by pathogens such as *Aspergillus flavus* and *A. niger*, which produce toxins known as aflatoxins that can contaminate the nuts, posing health risks to humans and animals if consumed. Symptoms of pod rot include dark, sunken lesions on the pods, often accompanied by mold growth. Infected pods may become shriveled, discolored and unsuitable for consumption or processing.

The diseases may occur alone or in combination. Rust has been known to cause significant yield losses, particularly when the two leaf-spot fungi also affect the crop (Subrahmanyam and McDonald, 1987). Factors like rainfall, humidity and soil moisture exacerbate the rapid dissemination of diseases during the seedling stage (Velásquez *et al.,* 2018; Dell'Olmo *et al.,* 2023). Effectively managing peanut diseases necessitates prompt and precise identification of disease types, as well as the timely implementation of appropriate control measures to protect yield and quality. Low-yielding varieties, a lack of high-yielding cultivars, suboptimal agronomic practices, climate change and limited input usage all contribute to low peanut production (Patayon and Crisostomo, 2022). Notably, prevalent peanut diseases such as early and late leaf spots exert a significant impact on production due to the warm and humid climate, leading to defoliation and yield losses ranging from 50% to 70% (Chaudhari *et al.,* 2019). Detecting diseases using manual methods can be challenging due to limited manpower and the lack of early identification methods. The visible diagnosis has significant drawback symptoms are only detectable when they become severe enough to manifest visibly, particularly in cases of element deficiency. By that time, a significant loss in yield had already occurred (Singh *et al.,* 2004; Andrew *et al.,* 2022; Wasik and Pattinson, 2024; Maltare *et al.,* 2023; Min *et al.,* 2024; Cho, 2024). Advancements in image analysis and machine learning (ML), particularly neural networks, have offered new opportunities for precise crop symptom detection (Waleed *et al.,* 2021). Convolutional Neural Networks (CNNs) have emerged as a key tool in identifying image patterns, especially for plant disease symptoms. One of the major pros of using ML lies in its ability to aid in precision farming by targeting specific areas affected by diseases, reducing the overall use of pesticides and resources (Roberts *et al.,* 2021). Moreover, automated disease detection through ML reduces the time and labour required for manual scouting, making the process more efficient (Raza *et al.,* 2020). It can achieve high accuracy, minimising false positives and negatives compared to traditional methods (Fuentes *et al.,* 2021).

Naoumi *et al.* (2024) proposed two methods for estimating angle of arrival and departure in bistatic ISAC systems: A deep learning (DL)-based approach and a parameterized algorithm. The DL-based method reduces input size and improves computational efficiency, demonstrating lower computational complexity and potential for real-world implementation. Delamou *et al.* (2023) introduced a new method for multitarget radar detection using a convolutional neural network. Their method estimates target range and velocity directly from detected signals, demonstrating superior accuracy and reduced prediction time compared to established methods.

Related work

To address the severe impact of peanut southern blight on production, Guo *et al.* (2023) conducted a hyperspectral analysis. The technique of hyperspectral imaging, also known as hyperspectral remote sensing, gathers and analyzes data from the entire electromagnetic spectrum. Unlike traditional imaging systems that capture data in a few spectral bands (such as red, green and blue), hyperspectral analysis involves acquiring and analysing data in many contiguous bands across the entire spectrum. The study was able to find out how bad peanut southern blight was by looking at leaf-level spectral data and using continuous wavelet transform (CWT) with machine learning. The support vector machine (SVM) model, utilising CWT as an input feature, demonstrated the highest accuracy, highlighting the potential of this method for accurate disease assessment.

Panda *et al.* (2021) applied RCNN method to effectively determine the leaf's health status, addressing challenges related to accuracy, time complexity and computational complexity. Kursun *et al.* (2023) studied groundnut disease detection using CNN and transfer learning. They built a dataset and used the AlexNet model through transfer learning. Their method showed high classification accuracy, proving CNN's effectiveness in detecting diseases. Feng *et al.* (2022) proposed an online method for identifying peanut leaf diseases. They used a data balancing algorithm and deep transfer learning to fix distribution issues. A lightweight CNN was applied, which achieved high accuracy in detecting different leaf diseases. This method offers a practical solution for real-time disease detection.

Zang *et al.* (2021) designed a testing system for peanuts. This system, utilising machine learning, demonstrated real-time measurement capabilities for peanut pods and nuts, significantly improving testing efficiency and accuracy compared to manual methods.

Patil *et al.* (2022) investigated the application of AI algorithms in plant disease prediction. Comparing various algorithms, they found that the artificial neural network (ANN) outperformed others, achieving an accuracy of 90.79% in predicting plant diseases based on temperature, moisture and humidity parameters. Vyas and Chaplot (2023) used deep learning technology for groundnut leaf disease identification. They employed three models (VGG16, AlexNet and Resnet50) using real-time data, with Resnet50 achieving the highest accuracy of 82.30%, providing valuable insights for disease identification in groundnut crops. Devi *et al.* (2020) proposed an image processing-based approach, named H2K, for detecting and classifying groundnut leaf diseases. The H2K method, incorporating the Harris corner detector, HOG and KNN classifier, demonstrated robustness and optimum performance, achieving an impressive accuracy of 97.67%. Yang *et al.* (2021) improved the VGG16 DCNN for peanut variety identification. The model achieved a high average accuracy of 96.7% in identifying and classifying different peanut varieties.

Deep learning models have become a valuable tool for decision-making in agriculture by utilizing large amounts of data collected from smart farm sensors. This technology can help meet the increasing agricultural demands worldwide. However, the complex and diverse agricultural environments pose a significant challenge to effectively testing and adopting new technologies. The present study attempts to develop a CNN architecture for the identification of leaf diseases caused by groundnut plants.

MATERIALS AND METHODS

Deep learning, using CNNs, processes groundnut leaf images through four main steps: Collecting data, building the model, training it and testing its accuracy.

Dataset

A proper dataset must be chosen to perform effective image detection, from training to performance analysis. This ensures accuracy and effectiveness in detecting leaf diseases through images. In this study, data is taken from the Mendeley database. This dataset specifically consists of images depicting five categories of groundnut leaves: early leaf spot, healthy, late leaf spot, nutrition deficiency and rust leaves (Aishwarya and Reddy, 2023). The dataset includes a total of 3058 images. These images are distributed among five categories as follows: early leaf spot (885), healthy (929), late leaf spot (689), nutrition deficiency (329) and rust (226) leaves. The early leaf spot

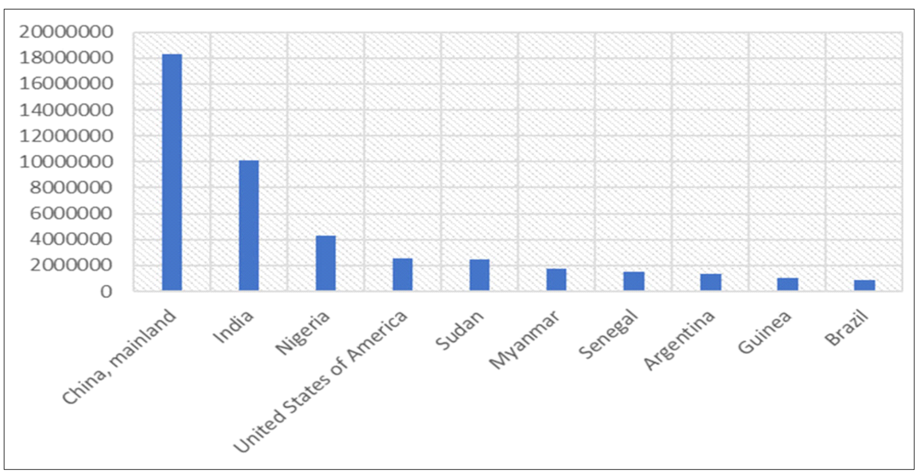
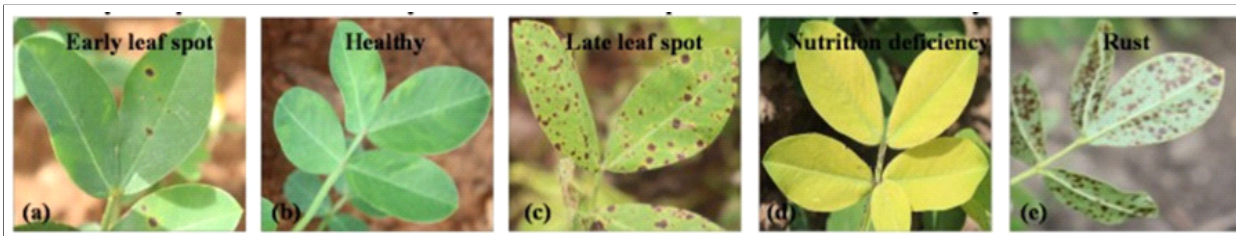


Fig 1: Leading Producers of groundnut (excluding shelled); Source: https://www.fao.org.



(a) Healthy (b) Early leaf spot (c) Late leaf spot (d) Nutrition deficiency and (e) Rust disease.

Fig 2: Images of groundnut plant leaves.

appears shortly after planting, which can be seen as damage on the inner surface of leaves, usually having a yellow circle surrounding a lighter brown color. During the rainy seasons, the disease spreads significantly. However, the mature fields have late leaf spots, usually 60 days after planting. Damage on leaves appears as tiny, round, dark brown patches with a carbon black color on both the upper and bottom surfaces and no yellow border (Kumar and Thirumalaisamy, 2016). Among nutritional deficiencies, iron and sulfur deficiencies are responsible for significant nutritional deficits. When sulfur is deficient, yellowing begins in the center leaves and moves up the plant. On the other hand, yellowing starts in the lower leaves and spreads to the younger leaves when there is a nitrogen shortage. Young plants' leaves first show signs of iron shortage when they turn a sickly white color from a lack of chlorophyll. However, a major agronomic strain that causes most of the yield loss is the groundnut rust disease, which lowers pod and fodder yields and degrades oil quality, causing decreased economic production. The rust disease grows best in moderate, humid settings, which when hydrated, can spread quickly because the spores can be carried by the wind or water. Wet surfaces are necessary for the spread of infections (Kankam *et al.,* 2022).

Image preprocessing, labelling and training dataset

To use images from the dataset for training, they are pre-processed. Resizing and rescaling were done to ensure all images had a uniform size, as they came from different sources. Larger images require more processing power, so resizing helps maintain accuracy and speeds up training. All images were standardized to 256 × 256 × 3 and then converted to grayscale. After resizing, groundnut leaf images were labeled based on their health condition. The dataset is split into training (80%), validation (10%) and testing (10%). Data augmentation was applied to the training set. This included random horizontal and vertical flips and rotations. Finally, the normalization of images is performed by scaling pixel values to the range [0, 1].

Model architecture

The neural network model was built using the TensorFlow Keras API. Its architecture possesses multiple convolutional and max-pooling layers, as shown in Fig 3. The final part of the model contains dense layers for classification. The input layer resizes all images to 256 × 256 pixels and normalizes pixel values. Several convolutional layers were used, with increasing filter sizes (64, 256, 512) and a 3x3 kernel size. ReLU activation functions were applied to add non-linearity. A max-pooling layer (2×2) is applied after each convolutional layer. A flatten layer was added to convert 2D feature maps into a 1D vector. This output is passed to dense layers. One dense layer with 64 units and ReLU activation was included. The final output layer has five neurons, one for each class and uses softmax activation for multi-class classification. The model was trained for 100 epochs with a batch size of 32. Training and validation accuracy were tracked for performance evaluation.

Convolution operations use filters, or kernels, to traverse an input image or feature map. Information is extracted from overlapping sections at each stage. The process involves mathematical operations, multiplying filter elements by input image elements and summarizing results. A two-dimensional convolution operation is represented by an input image (I) and a kernel (K) as follows:

$$S_{(i,j)} = \sum^{m-1} \sum^{n-1} I_{(i+p,\, j+q)}\, K_{(p,q)}$$

Where,
m and n = Kernel (K) coordinates.
i and j = Image (I) coordinates.

The model uses a max pooling layer to reduce computational complexity and overfitting risk. The Fully Connected Layer classifies images based on learned patterns from previous layers. The fully connected layer with a Softmax function predicts and assigns probabilities to classes, ensuring robust and interpretable classification of input data. The softmax function transforms the numerical values of the neurons in the previous layer, $y_1, y_2, y_3 \ldots y_n$, into probabilities, $P_1, P_2, P_3 \ldots P_n$, given n.

$$P_k = \frac{e^{yk}}{\sum_{j=1}^{n} e^{yj}}$$

Where,
y_k = Numerical value of the j^{th} neuron in the preceding layer.
P_k = Probability of class k following the application of softmax.

Flattens the input into a one-dimensional array. It doesn't have any parameters. In summary, the process starts with an input shape of (32, 256, 256, 3) for a batch of 32 images with a size of 256×256 pixels and 3 color channels. The model consists of convolutional layers, max-pooling layers and dense layers, culminating in a total of 2,125,061 trainable parameters. The goal of this architecture is likely image classification, where the model learns to extract features and make predictions based on the provided classes.

The softmax function is often used in the output layer of neural networks for classification applications as it gives the network's output a probability interpretation. It aids with the following aspects of classification.

Probability interpretation

The softmax function receives logits that are generated by the neural network. Every score is converted into a probability that indicates the possibility of the input being a member of a certain class. This understanding of probability enhances the output's ability and facilitates learning.

Normalization

The softmax function ensures that the output probabilities will collectively add up to one for all classes. This attribute is essential for tasks involving classification as it verifies that the output of the model accurately reflects an accurate probability distribution. When the probabilities add up to one, they represent the relative probability of each class, which aids the comparison and interpretation of the model's predictions.

Gradient-based optimization

The differentiability of the softmax function enables efficient gradient-based optimization methods, such as back propagation, during the training phase. The neural network acquires the most suitable parameters (weights and biases) by modifying them according to the discrepancy between the expected probability and the actual labels.

Multi-class classification

Softmax is especially valuable for multi-class classification problems in which the input may be assigned to one of many incompatible classes. Through the generation of a probability distribution comprising all possible classes, the softmax function allows the model to make well-informed decisions about the most probable class for an input.

Evaluation parameters

Convolutional neural networks (CNNs) are examined using multiple key variables to determine their performance in solving specific tasks. Here are some commonly used evaluation parameters for CNNs:

Accuracy

The percentage of images that are accurately classified. Although it can be misleading for unbalanced datasets, this measure is straightforward but effective.

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

Precision

The percentage of positive cases that are positive compared to those that are predicted. shows the extent to which the model avoids false positives.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall

The percentage of true positive cases that are correctly identified. shows the degree to which the model can identify true positives.

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-score

It combines precision and recall into a single value and is especially useful when there is an uneven class distribution.

$$\text{F1 - Score} = \frac{2^{*}\ \text{Precision}\ ^{*}\ \text{Recall}}{\text{Precision} + \text{Recall}}$$

RESULTS AND DISCUSSION

The accuracy and loss comparison for training and validation are shown in Fig 4 (a, b). After 100 epochs, the model reached a training accuracy of 91.94%. The training loss was 0.1926, showing the model fit the data well. On the validation dataset, the accuracy was 90.97% and the loss was 0.2275. This shows the model can generalize well to new data. The results confirm that the model learned effectively. More training epochs could

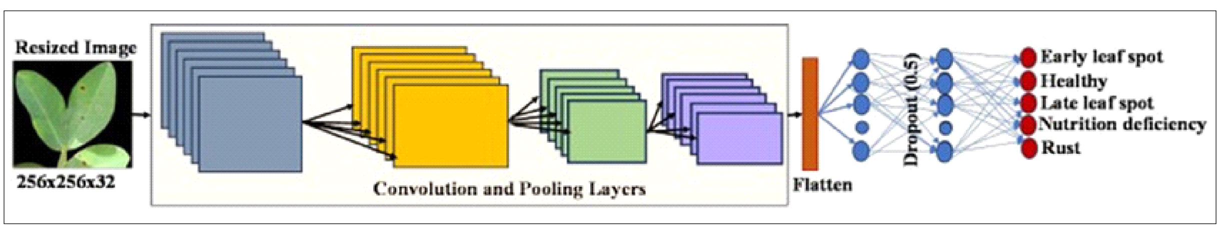


Fig 3: Model architecture: Convolution, pooling layers, flatten and dropout specifications.

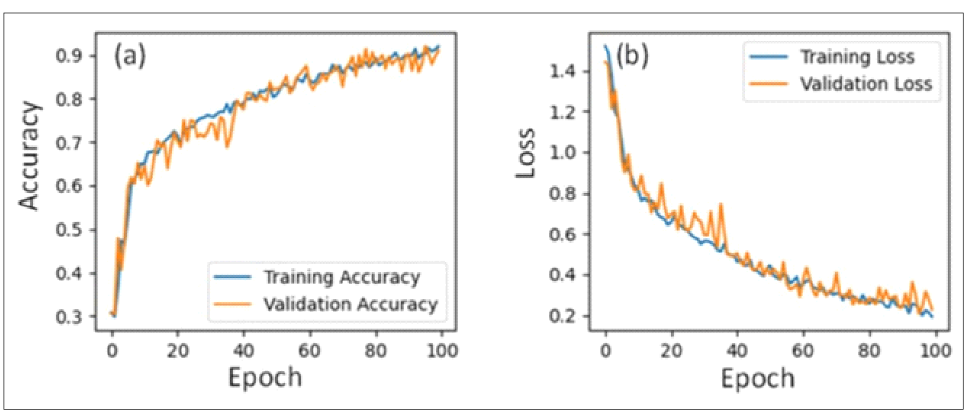


Fig 4: Accuracy and loss trends for both training and validation datasets.

further improve accuracy but would increase training time.

Fig 5 illustrates predictions from the CNN model on groundnut leaf images. Each image displays the actual label, the predicted class and the confidence level. The displayed samples include early leaf spot, late leaf spot, nutrition deficiency (each with 100% confidence) and rust (80.77% confidence). These examples highlight the model's capability to accurately detect and classify various leaf diseases.

The confusion matrix for the category with five classes of groundnut leaf disease is shown in Fig 6. The columns show the expected labels for the data points, whereas the rows show the true labels. The accurately classified data points are shown by the diagonal elements and the incorrectly classified data points are shown by the off-diagonal elements. Table 2 displays the evaluation metrics for the classification model for each of the classes. The metrics include precision, recall, F1-score and support. In comparing the performance metrics across different classes distinct patterns are observed. For the Early leaf spot class, the model's precision of 0.8889 is remarkable indicating that it can accurately identify cases that fall into this category.

Still, with a recall of 0.7843, it indicates a modest capacity to capture all real occurrences of this class. After adjusting for precision and recall, the final F1-score is 0.8333. The model retains a strong precision of 0.8640 for the Healthy leaf class, with a recall of 0.9076. this class has a significantly higher F1-score of 0.8852, indicating that recall and precision are well-balanced. The Late leaf spot class performed well, attaining recall 1.0 and precision of 0.9872) resulting in an F1-score of 0.9935. The model appears to predict this class with a high degree of accuracy. For the Nutrition deficiency class, the precision is at 0.9211, indicating a good degree of prediction accuracy. The model obtains an F1-score of 0.9589 with recall 1.0. The "Rust" class shows a precision of 0.9048 for the model. The F1-score of 0.9500 is significant and this can be explained by the recall of 1.0, which is comparable to other classes. The overall accuracy of the model is 90.625%. The model was able to correctly identify the proper class for the majority of the images in the dataset, as evidenced by the high ~ 0.91 average precision, recall and F1 score. Still, the model did slightly better in a few classes than others.

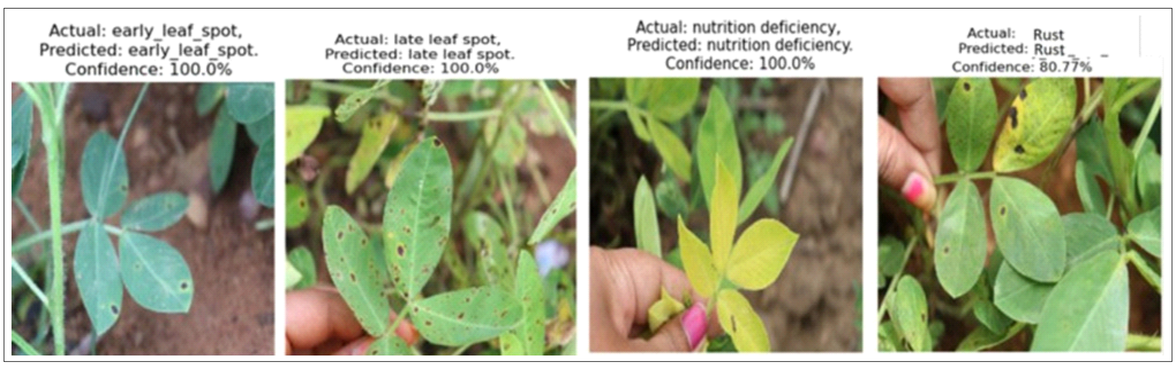


Fig 5: The actual and predicted diseases with confidence score.

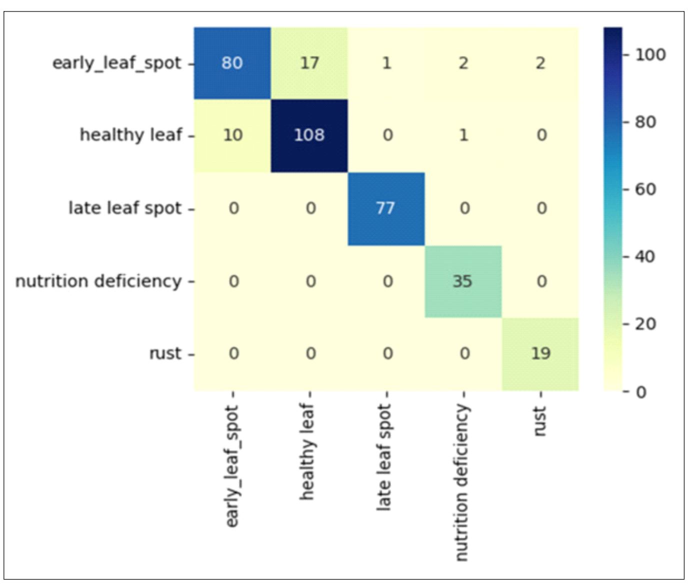


Fig 6: Confusion matrix for five classes of groundnut leaf disease.

Table 1: Configuration details of the CNN model used for sugarcane leaf disease classification.

Parameter	Description
Number of convolutional layers	6 layers with filter sizes of 64, 256 and 512
Number of max pooling layers	6 layers with a pooling size of (2, 2)
Dropout rate	0.5
Network weight initialization	Uniform
Activation function	ReLU
Epochs	100
Batch size	32
Learning rate	0.0001
Image size	256 × 256 pixels

Table 2: Classification results for each disease class.

Label	Precision	Recall	F1-score	Support
Early leaf spot	0.8889	0.7843	0.8333	102
Healthy leaf	0.8640	0.9076	0.8852	119
Late leaf spot	0.9872	1.000	0.9935	77
Nutrition deficiency	0.9211	1.000	0.9589	35
Rust	0.9048	1.000	0.9500	19
Accuracy			0.9062	352
Macro avg	0.9132	0.9384	0.9242	352
Weighted avg	0.9060	0.9062	0.9047	352

Limitations and future work

- The limitation of this work is, the dataset used in this study has 3058 images with five classifications. A large number of images can be used in further work.
- This study focused on four major leaf diseases in groundnut. However, groundnuts also face other threats, including stem and root infections. Future research should address a wider range of diseases affecting different plant parts.

CONCLUSION

This study demonstrated the deep learning algorithms' capacity to accurately detect plant diseases and nutritional deficiencies using leaf images. The model's accuracy and precision show its practical importance since timely treatments in agriculture rely on early identification and precise plant disease classification. The extensive assessment of the model's performance throughout a wide range of classes provides further evidence of its effectiveness and reliability. To ascertain the model's applicability in agricultural contexts, more testing of its performance in real-world settings with various plant phenotypes and environmental factors would be beneficial.

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Authors' contributions

The authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all aspects of this work.

Data availability statement

The data is available on Mendeley database site.

Declarations

Author(s) declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

There is no conflicts of Interests of authors.

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