Data in Brief 55 (2024) 110763

Contents lists available at ScienceDirect

Data in Brief

journal homepage: www.elsevier.com/locate/dib

Data Article

A novel groundnut leaf dataset for detection and classification of groundnut leaf diseases

Buddhadev Sasmal[a,b], Arunita Das[b], Krishna Gopal Dhal[b], Sk. Belal Saheb[c], Ruba Abu Khurma[d,e], Pedro A. Castillo[f,*]

[a] *Department of Pure and Applied Science, Midnapore City College, Paschim Medinipur, West Bengal, India*
[b] *Department of Computer Science and Application, Midnapore College (Autonomous), Paschim Medinipur, West Bengal, India*
[c] *Zapuza Technologies LLP, Midnapore, West Bengal, India*
[d] *MEU Research Unit, Faculty of Information Technology, Middle East University, Amman, 11831, Jordan*
[e] *Applied Science Research Center, Applied Science Private University, Amman 11931, Jordan*
[f] *Department of Computer Engineering, Automatics and Robotics, University of Granada 18071, Spain*

A R T I C L E I N F O

Article history:
Received 13 February 2024
Revised 6 July 2024
Accepted 15 July 2024
Available online 20 July 2024

Dataset link: Groundnut Dataset (Original data)

Keywords:
Groundnut
Peanut
Deep learning
Image classification
Disease detection
Precision griculture

A B S T R A C T

Groundnut (Arachis hypogaea) is a widely cultivated legume crop that plays a vital role in global agriculture and food security. It is a major source of vegetable oil and protein for human consumption, as well as a cash crop for farmers in many regions. Despite the importance of this crop to household food security and income, diseases, particularly Leaf spot (early and late), Alternaria leaf spot, Rust, and Rosette, have had a significant impact on its production. Deep learning (DL) techniques, especially convolutional neural networks (CNNs), have demonstrated significant ability for early diagnosis of the plant leaf diseases. However, the availability of groundnut-specific datasets for training and evaluation of DL models is limited, hindering the development and benchmarking of groundnut-related deep learning applications. Therefore, this study provides a dataset of groundnut leaf images, both diseased and healthy, captured in real cultivation fields at Ramchandrapur, Purba Medinipur, West Bengal, using a smartphone camera. The dataset contains a total of 1720 original images, that can be utilized to train DL models to detect groundnut leaf diseases at an early stage.

* Corresponding author.
E-mail address: pacv@ugr.es (P.A. Castillo).

https://doi.org/10.1016/j.dib.2024.110763

Additionally, we provide baseline results of applying state-of-the-art CNN architectures on the dataset for groundnut disease classification, demonstrating the potential of the dataset for advancing groundnut-related research using deep learning. The aim of creating this dataset is to facilitate in the creation of sophisticated methods that will aid farmers accurately identify diseases and enhance groundnut yields.

Specifications Table

Subject	Computer Science, Agricultural Science
Specific subject area	Computer Vision and Deep Learning techniques for the early detection and classification of groundnut leaf diseases.
Data Format	Leaf image data in .jpg format
Type of data	Image
Data collection	Groundnut leaf images were collected using Redmi Note 8 Pro smartphone cameras with 64-megapixel and aperture f/1.9. Images of diseased and healthy groundnut crop leaves were captured separately. The images of diseased leaves were classified based on their symptoms. The dataset contains Leaf Spot (Early and Late), Alternaria Leaf Spot, Rust, and Rosette diseases of groundnut crop. Images were taken in the field over a four-month period. Images were manually taken using a smartphone and categorised based on disease criteria with the assistance of a pathologist.
Data source location	Ramchandrapur, Purba Medinipur, West Bengal, India, Pin: 721429 Latitude 21.930146 and Longitude 87.556852
Data accessibility	Repository name: Mendeley Data. Data identification number: DOI: 10.17632/x6x5jkk873.2 Direct URL to data: https://data.mendeley.com/datasets/x6x5jkk873/2 Instructions for accessing these data: All the image can be downloaded by the following link: https://data.mendeley.com/datasets/x6x5jkk873/2

1. Value of the Data

- We address four prominent diseases that specifically target groundnut leaves, causing significant damage to numerous groundnut fields. Researchers and practitioners can download the dataset, which is openly available and accessible for public use, and input the data straight into deep learning models.
- Groundnut leaf disease datasets are valuable for precision agriculture. The dataset images were collected in real time environment, leading to a range of variables, such as the background and the various orientations and distances of the images.
- The detection of groundnut leaf disease in agriculture has various uses, providing farmers with the advantages of early identification of the disease, less chemical consumption, crop monitoring, and quality assurance. The proposed dataset facilitates the advancement of sophisticated models and the evaluation of methodologies within the scientific community.
- The dataset can be utilized for several ML and DL models, including those used for disease identification and classification, leaf area segmentation, infected area segmentation, and many more tasks.
- Since the images were captured in real scenario, the dataset provides a tough context for the researchers to classify and identify groundnut leaf diseases. The presented dataset can be utilized to develop tools for identifying groundnut leaf diseases, which can subsequently assist farmers in improving the cultivation of the groundnut crop.

The primary contribution of this study, as well as the significant gaps in existing research and how this study addresses them, are presented in the table below:

Main questions/Gaps	How this study addresses them
Lack of groundnut-specific datasets for DL model training and evaluation.	This study presents an extensive collection of 1720 images of groundnut leaves, encompassing both diseased and healthy leaves. These images were acquired in actual cultivation areas, providing a realistic representation of the plant's condition.
Limited research on early diagnosis of groundnut leaf diseases using DL techniques.	The dataset facilitates the creation of DL models, specifically CNNs, to identify groundnut leaf diseases in their early stages.
Benchmarking DL applications for groundnut leaf disease detection.	The presented baseline results showcase the potential of the dataset for advancing research in this field by implementing state-of-the-art CNN architectures.
Need for practical tools to assist farmers in disease identification.	This work intends to assist farmers in improving groundnut yields by enabling the development of advanced DL models that can effectively identify diseases.

2. Background

Datasets play a crucial role in DL tasks [1] as they provide the basis for training and evaluating DL models. A high-quality dataset is essential for the successful development of accurate and robust deep learning models. Therefore, the objective of generating a groundnut leaf dataset is to create an extensive assortment of groundnut leaf images that can be utilized to train, validate, and test DL models for disease detection and diagnosis tasks [2]. The dataset was collected from West Bengal, India. This dataset gives a solution for early identification of diseases of groundnut crops, which will contribute to addressing the challenges of food security and promoting economic growth [3] of farmers in West Bengal, India, and around the world. The groundnut leaf dataset that is developed will serve as a significant resource for researchers and agronomists to construct sophisticated DL models for the early identification, precise diagnosis, and effective management of diseases in groundnut crops. The main goal of creating a groundnut leaf dataset for DL is to support the improvement of groundnut crop health, promote sustainable groundnut production methods, and enhance food security in regions where groundnut is a crucial crop.

3. Data Description

This paper provides an image database of groundnut leaves collected from agricultural land in West Bengal, India, that are both healthy and infected with Leaf spot (early and late), Alternaria leaf spot, Rust, and Rosette. The dataset contains 1,720 jpg images in 4624×3472 pixel format, each labelled with the image number and the name of the image. Data were uploaded to the repository in 5 distinct folders: 1 folder for healthy data, 1 folder for Leaf spot (early and late), 1 folder for Alternaria leaf spot, 1 folder for Rust, and 1 folder for Rosette diseases. In addition, each folder's name reflected the associated image class. The HEALTHY folder comprises a collection of images depicting groundnut leaves in a healthy condition. The LEAF SPOT (EARLY AND LATE) folder contains images of groundnut leaves affected by Leaf spot (early and late). The folder titled ALTERNARIA LEAF SPOT contains images depicting groundnut leaves that have been infected by Alternaria leaf spot. The RUST folder comprises images of groundnut leaves infected by Rust disease. The ROSETTE folder contains images of groundnut leaves infected by Rosette disease. The images were divided into distinct directories to facilitate the process of sharing and downloading data. For the procedure of identifying leaf diseases, the most frequently affected diseases are selected. Table 1 depicts the total number of images that correspond to every disease group.

Table 1
The number of images for every groundnut disease group.

Class name	Number of images
Healthy	600
Leaf spot (Early and Late)	450
Alternaria leaf spot	450
Rust	120
Rosette	100
Total	**1720**

Fig. 1. Leaf spot (Early and Late).

3.1. Description of major groundnut leaf diseases and symptoms

Groundnut is susceptible to several leaf diseases that can significantly impact its quality and yield. Severe infections can lead to premature defoliation, reducing the plant's ability to produce and fill pods, ultimately lowering yield. Disease-infected plants often produce smaller, lower-quality nuts. Additionally, diseases like rust and leaf spots can cause blemishes on the shells, reducing market value. A brief description of the different leaf diseases that affected groundnut crops are given below.

3.1.1. Leaf spot (early and late)

Groundnut leaf spot (early and late) [4] is a fungal disease that affects most groundnut cultivation. The pathagon Cercospora arachidicola is responsible for early leaf spot. Early leaf spot is a serious disease that affects groundnut plants and can cause a significant decrease in crop yield if not effectively controlled. Symptoms of groundnut early leaf spot usually appear on the lower leaves of the plant as small, circular spots that are initially yellow or light brown and later turn dark brown or black. These spots may coalesce and form larger lesions, and can be encircled by a yellow ring. When the disease grows, the leaves may become necrotic, withered, and eventually drop untimely. Severely affected plants may show stunted growth, reduced pod development, and can experience significant yield losses.

The plant pathogen Phaeoisariopsis is responsible for the late leaf spot. It is among the most harmful diseases of groundnut and can cause significant yield losses if not effectively managed. The signs of groundnut late leaf spot typically appear on the lower leaves of the plant, like early leaf spot. However, late leaf spot lesions are usually larger, with a diameter ranging from 1 to 10 mm, and are typically circular shaped. The lesions start as small, brown spots and gradually enlarge to form necrotic lesions with a reddish-brown to black color encircled by a faint yellow ring or without a ring. In extreme cases, the lesions can merge and cover a large portion of the leaf surface. Infected leaves may become chlorotic, wither, and prematurely defoliate, leading to reduced photosynthesis, stunted growth, and lower pod development, resulting in significant yield losses. Fig. 1 shows the sample of early and late leaf spot.

Fig. 2. Alternaria Leaf Spot.

Fig. 3. Rust Disease.

3.1.2. Alternaria leaf spot

Alternaria leaf spot [5] is a foliar disease produced by the fungus Alternaria species that affects groundnut leaves. It is a common disease that can cause significant yield losses if not properly managed. The symptoms of A. tenuissima are characterised by light to dark brown discoloration of the apical portions of leaflets. A. arachidis causes brown, irregularly shaped lesions that are surrounded by yellow haloes. During the advanced stages of infection, affected leaves wither and become fragile, while also curling inward. A. alternata produces small, pale, water-soaked sores that spread throughout the surface of the leaves. The lesions become necrotic and brown and range in shape from round to irregular. In severe cases, the lesions can cover a large portion of the leaf surface, leading to premature defoliation and reduced photosynthesis which reduce groundnut production. The sample of groundnut Alternaria leaf disease shown in Fig. 2.

3.1.3. Rust disease

Groundnut rust disease [6], scientifically referred to as Puccinia arachidis, is a fungal disease that specifically targets groundnut crops. It is a common disease that can result in substantial reductions in crop production if not effectively managed. Warm, wet weather facilitates its spread. All the plant's aerial sections are attacked by the disease. Typically, the disease is detected when plants are approximately six weeks old. On the underside of leaves, dusty pustules ranging from brown to chestnut emerge. The epidermis ruptures, exposing a multitude of uredospores in powdery form. On the upper surface of leaves, minute brown necrotic spots appear to correspond with the sori. On the petiole and stem, there are rust pustules. Towards the end of the season, brown teliospore appear as dark pustules among the necrotic regions. In severe infections, lower leaves shrivel and fall prematurely. The severe infection causes the development of seeds that are small and shrivelled. Fig. 3 shows the sample of groundnut rust disease.

Fig. 4. Rosette Disease.

Fig. 5. Healthy groundnut leaf.

3.1.4. Rosette disease

Groundnut rosette disease [7], also known as groundnut rosette virus disease, is a virus disease that infected groundnut leaves, produced by the groundnut rosette virus. It is a serious disease that can cause significant yield losses in groundnut production. Symptoms of groundnut rosette disease can vary depending on the stage of infection. Initial symptoms may manifest as chlorosis and leaf curling, accompanied by stunted plant growth. The infected plants may exhibit a characteristic "rosette" appearance, with small, misshapen leaves and shortened internodes, giving the plant a bushy, compact appearance. The leaves may exhibit dieback or necrosis, as well as mottling and distortion, as the condition worsens. The disease can cause reduced the development of flower and pod, and severely affected plants may not produce any viable pods, leading to complete crop loss. The sample of groundnut rosette disease shown in Fig. 4.

3.1.5. Healthy leaf

A healthy groundnut leaf is typically characterized by its vibrant green color, symmetrical shape, smooth texture, firmness, appropriate size, absence of pests or diseases, and secure attachment to the plant. A healthy groundnut leaf indicates that the plant is actively photosynthesizing and efficiently exchanging gases and transpiring. It also suggests that the plant is receiving adequate nutrients, water, and sunlight, and is not under stress from pests, diseases, or environmental factors. The presence of healthy groundnut leaves is essential for facilitating the plant's growth and development, which ultimately results in increased yields and improved crop quality. Regular monitoring of groundnut leaves for signs of pests, diseases, or nutrient deficiencies, and taking prompt measures for management, can help ensure that the leaves remain healthy, contributing to optimal groundnut plant performance and yield. Fig. 5 depicts sample images of healthy groundnut leaves.

The names and symptoms of the groundnut leaf diseases, as well as an estimate of when each disease is most likely to appear, are included in Table 2.

Table 2
Types of groundnut diseases.

Disease selected	Symptoms	Disease attack duration
Leaf spot (Early and Late)	In early leaf spot, small, circular spots that are initially yellow or light brown and later turn dark black or brown and encircled by a yellow ring.	1 month after seed sowing
	In late leaf spots, small, brown spots gradually enlarge to form necrotic lesions with a reddish-brown to black colour, surrounded by a faint yellow halo or without a halo.	6 – 7 weeks after seed sowing
Alternaria leaf spot	Small, chlorotic, water-soaked lesions are visible on both leaf surfaces. Leaves become brittle and inwardly curled.	5 – 6 weeks after seed sowing
Rust	Dusty pustules ranging in colour from brown to chestnut occur on the undersides of leaves. Brown teliospore appear as dark pustules among the necrotic regions.	After 6 weeks from the seed sowing
Rosette	Yellowing and curling of the leaves, along with stunting of plant growth, which can progress to a characteristic “rosette” appearance.	2 – 3 weeks after seed sowing

3.2. Significance of the dataset

The dataset serves as a valuable resource for precisely recognizing and controlling diseases that impact groundnut leaves. Additionally, it aids in the development of effective disease control strategies. The dataset contains a diverse array of information that aids in the development of models for early detection of diseases. This enables timely intervention to mitigate the adverse impact on peanut harvests. Researchers and precision agriculture professionals can employ the dataset to enhance farming operations by ensuring accurate and effective allocation of resources for disease diagnosis and management. The collection supports scientific endeavors, fostering innovation in the fields of agriculture, plant pathology, and data science. It functions as a foundation for exploring novel methodologies and approaches.

4. Experimental Design, Materials and Methods

Dataset preparation is a critical aspect of building effective DL models [8], and it can have a significant impact on the performance, generalization, and reliability of the models. A well-prepared dataset is essential for training models that not only perform well on the training set but also generalize effectively to new and unseen data. The process of groundnut dataset creation involved several stages, including image acquisition, image pre-processing, image augmentation, image partitioning, and image classification. Each stage in this process plays a crucial role in ensuring that the data fed into the deep learning model is of high quality and diversity. Fig. 6 shows the workflow of the dataset preparation stages.

4.1. Image acquisition

Image acquisition is of utmost importance in deep learning due to its profound impact on the performance and effectiveness of models. DL models depend on extensive sets of annotated data to acquire patterns and generate precise predictions [9]. At this phase, high-definition digital cameras or smart phones can be utilized to obtain images of diseased as well as healthy leaves in the fields. In this work, Redmi smartphones were used to take images of groundnut leaves. Afterwards, all the images in the collection were categorised with the assistance of a

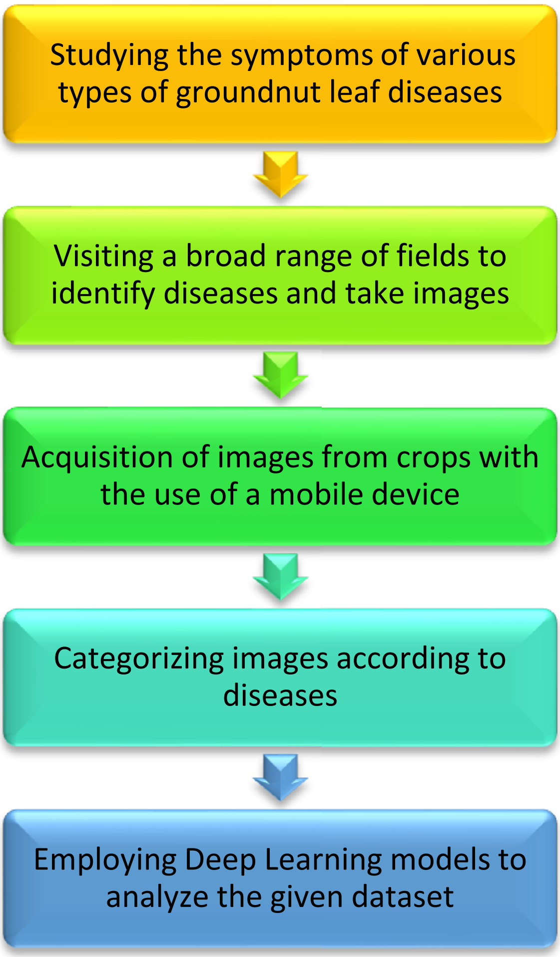

Fig. 6. Workflow of the groundnut leaf dataset preparation stages.

pathologist who provided disease descriptions. The Purba Medinipur district in West Bengal is well-known for producing groundnut [10]. Therefore, between January-April of 2022 and 2023, a few trips were made to Ramchandrapur village in the Purba Medinipur district of West Bengal, where groundnuts are grown during that particular season. According to the pathologist, Leaf Spot (Early and Late), Alternaria Leaf Spot, Rust, and Rosette are among the most prevalent diseases of groundnut crops that have been identified and captured. A total of 1720 images were gathered, and Section 4 provides information on each disease type.

4.2. Image Preprocessing

4.2.1. Cropping and resizing

The importance of image preprocessing in DL cannot be overstated, as it greatly improves the performance [11] and accuracy of the model [12]. Preprocessing techniques are applied to images before feeding them into the DL model. The original groundnut leaf images had varying dimensions. Following that, every image contained in the dataset was analyzed for the square dimensions. Subsequently, a cropping tool was applied to non-square images in order to obtain the full leaf area with squared dimensions. Additionally, all the images were resized to 224 $\times$ 224 for further analysis.

4.2.2. Image augmentation

Image augmentation [13] is an essential technique in deep learning due to its importance in increasing the diversity and quantity of training data. By applying various image augmentation methods to existing images, such as rotation, scaling, flipping, cropping, and adding noise, image augmentation creates additional training samples that possess similar characteristics to the original data but exhibit slight variations. But it is also important to carefully select and apply image augmentation techniques based on the specific problem and domain, and to validate the effect of augmentation on the model's efficiency. It is often a matter of striking the right balance between diversity and realism while considering the limitations and requirements of the specific deep learning task. As the dataset contains a sufficient number of images to adequately test the performance of deep learning models, no augmentation method is applied. However, the researcher may use image augmentation method enhance model performance, improve generalization, prevent overfitting, and address any data imbalances that may exist.

4.3. Preliminary study

4.3.1. Proposed preliminary study

ML and DL models have demonstrated great efficacy for feature extraction and classification in image analysis tasks. In ML, feature extraction is a crucial step in building any pattern recognition and aims to acquire the relevant data that categorises every class. DL models [14], such as CNNs, have demonstrated outstanding efficacy in tasks related to the classification of images by leveraging their hierarchical architectures to capture and represent increasingly abstract features at different layers. Four pre-trained DL models namely, InceptionV3, ResNet50, DenseNet201 and AlexNet are utilized in this study to identify the various types of groundnut leaf disease.

InceptionV3 [15] model was introduced by Google researchers in 2015. It is a widely used architecture for image classification tasks, and it has demonstrated exceptional efficiency on various benchmarking datasets. The Inception module, which forms the building block of InceptionV3, enables the network to gather details at various spatial scales by using a combination of distinct filter sizes (1×1, 3×3, 5×5) and pooling procedures. ResNet50 [16] was developed by researchers of Microsoft in 2015. This model belongs to the ResNet family and is recognized for its capacity to effectively train networks with a large number of layers, while addressing the issue of the vanishing gradient. The ResNet50 is a 50-layer CNN model made up of 48 convolutional layers, one average pool and one MaxPool layer.

DenseNet201 [17] was introduced by researchers at the Visual Computing Group at Stanford University in 2017. This network architecture is characterized by its depth and high level of expressiveness, resulting in exceptional efficiency on a wide range of tasks related to computer vision. The architecture of DenseNet201 is based on the concept of dense connectivity. In DenseNet, every layer has a direct connection to each subsequent layer in a feed-forward method. AlexNet [18] is a popular CNN model that was presented by Krizhevsky et al. in 2012. It was a groundbreaking model that achieved significant improvement in image classification accuracy and played a pivotal role in popularizing DL for the tasks related to computer vision. The AlexNet model comprises eight layers; five of these layers are convolutional, and the remaining three are fully connected layers.

A total of 1720 original images were gathered and subsequently categorized into five distinct categories. The images were then separated into training, testing, and validation sets, with each category following an 80:10:10 ratio. For instance, Alternaria Leaf Spot has 360 training images, 45 validation images, and 45 test images. The training set contained a total of 1376 images, whereas the validation set contained 172 images, and the testing set contained 172 images. The

Table 3
The classification results of the utilized CNN models.

Model Name	Input Size	Accuracy	Precision	Recall	F1 Score
InceptionV3	224 × 224	96.51%	97.34%	99.04%	98.18%
ResNet50	224 × 224	86.04%	88.56%	86.78%	87.66%
DenseNet201	224 × 224	92.30%	93.82%	95.26%	94.53%
AlexNet	224 × 224	84.88%	86.35%	85.73%	86.03%

preliminary study was conducted using a Windows 11 PC, 16 GB RAM, 64-bit OS, with 4 GB RTX GeForce 3050 GPU. The Keras 2.4.3 framework and TensorFlow backend were utilized to facilitate the training and validation procedures of the deep neural networks.

4.3.2. Evaluation parameters

Performance evaluation parameters in DL are essential metrics that help assess the effectiveness of a model in solving a specific task. These parameters provide quantitative measures of how well a deep learning model is performing, and they play a crucial role in understanding and improving the model's capabilities. Once the models have been trained using the dataset, they are assessed using a range of performance parameters including accuracy, precision, recall, and F1 score. Accuracy is the measure of how accurately a model predicts the output class of an input image. If the model achieves this, it indicates that the model has been trained with high efficiency and is deemed suitable for validation.

The evaluation of a model's efficiency hinges significantly on the metrics of precision and recall. Precision evaluates the correctness of positive predictions by calculating the true positives divided by the sum of true positives and false positives. It indicates the model's ability to accurately identify instances of the positive class. On the other hand, recall is used to measures the model's capability to identify all actual positive cases by dividing true positives by the sum of true positives and false negatives. The F1 score, which is a harmonic mean of precision and recall, provides a balanced evaluation of a model's performance by giving equal consideration to false positives and false negatives. The F1 score is particularly valuable in situations where precision and recall need to be weighed against each other. Ultimately, the choice of metric depends on the specific objectives of the task at hand, with precision, recall, and F1 score collectively providing a nuanced understanding of a model's classification efficiency. These can be computed by applying the Eqs. (1-4) [19].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

4.3.3. Result of the preliminary study

The results obtained from these four different classification algorithms are presented in Table 3. The highest accuracy, precision, recall and F1 score value was achieved by InceptionV3 model with 96.51%, 97.34%, 99.04%, and 98.18%, respectively. Among all the utilized models, the AlexNet model obtained the lowest accuracy, precision, recall, and F1 score value with 84.88%, 86.35%, 85.73%, and 86.03%, respectively.

The aforementioned results make it very evident that the InceptionV3 model performed effectively for groundnut leaf disease identification. The dataset contains real-world scenarios that can assist the algorithm in effectively dealing with various situations. This leads to enhanced accuracy in recognition and facilitates the improvement and development of the algorithm. Consequently, this will make it possible for researchers to train more sophisticated algorithms [20]. The release of this dataset aims to expedite the development of an efficient automated system for detecting groundnut leaf diseases, thus significantly advancing the field of precision agriculture.

Limitations

Not applicable.

Ethics Statement

This study did not conduct experiments involving humans and animals.

CRediT Author Statement

The authors confirm contribution to the paper as follows: study conception and design: B. Sasmal, A. Das and S. Belal-Saheb; data collection: B. Sasmal, A. Das and K. Gopal-Dhal; analysis and interpretation of results: B. Sasmal; draft manuscript preparation: B. Sasmal, R. Abu-Khurma and P.A. Castillo. All authors reviewed the results and approved the final version of the manuscript.

Data Availability

Groundnut Dataset (Original data) (data.mendeley.com).

Acknowledgements

This work was supported by the Ministerio Español de Ciencia e Innovación under projects PID2020-115570GB-C22 MCIN/AEI/10.13039/501100011033 and PID2023-147409NB-C21 MICIU/AEI/10.13039/501100011033, the C-ING-027-UGR23 project and the Cátedra de Empresa Tecnología para las Personas (UGR-Fujitsu).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] J.G.A. Barbedo, Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification, Comput. Electron. Agric. 153 (2018) 46–53.
[2] M.P. Vaishnnave, K. Suganya Devi, P. Ganeshkumar, Automatic method for classification of groundnut diseases using deep convolutional neural network, Soft. comput. 24 (2020) 16347–16360.
[3] M.T. Variath, P. Janila, Economic and academic importance of peanut, in: Peanut Genome, 2017, pp. 7–26.
[4] F. Kankam, I.B. Akpatsu, T.K. Tengey, Leaf spot disease of groundnut: a review of existing research on management strategies, Cogent. Food Agric. 8 (1) (2022) 2118650.
[5] N. Kumar, R. Dutta, B.C. Ajay, T. Radhakrishnan, Alternaria leaf blight (Alternaria spp.)–an emerging foliar fungal disease of winter-summer groundnut (Arachis hypogaea): a review, Indian J. Agric. Sci. 92 (9) (2022).

[6] Y. You, J. Liao, Z. He, M. Khurshid, C. Wang, Z. Zhang, Y. Xia, Effects of peanut rust disease (Puccinia arachidis Speg.) on agricultural production: current control strategies and progress in breeding for resistance, Genes (Basel) 15 (1) (2024) 102.
[7] D.K. Okello, L.B. Akello, P. Tukamuhabwa, T.L. Odong, M. Ochwo-Ssemakula, J. Adriko, C.M. Deom, Groundnut rosette disease symptoms types distribution and management of the disease in Uganda, Afr. J. Plant Sci. 8 (3) (2014) 153–163.
[8] A. Munappy, J. Bosch, H.H. Olsson, A. Arpteg, B. Brinne, Data management challenges for deep learning, in: 2019 45th Euromicro Conference on Software Engineering and Advanced Applications (SEAA), IEEE, 2019, pp. 140–147.
[9] M. Deb, K.G. Dhal, R. Mondal, J. Gálvez, Paddy disease classification study: a deep convolutional neural network approach, Opt. Memory Neural Netw. 30 (2021) 338–357.
[10] G.W. Bengal, District wise estimates of yield rate and production of nineteen major crops of West Bengal during 2014–15, Bureau Appl. Econ. Statistics (2016) 1–243.
[11] B.A. Hassan, T.A. Rashid, S. Mirjalili, Performance evaluation results of evolutionary clustering algorithm star for clustering heterogeneous datasets, Data Brief. 36 (2021) 107044.
[12] M. Deb, A. Garai, A. Das, K.G. Dhal, LS-Net: A convolutional neural network for leaf segmentation of rosette plants, Neural Comput. Appl. 34 (21) (2022) 18511–18524.
[13] M. Xu, S. Yoon, A. Fuentes, D.S. Park, A comprehensive survey of image augmentation techniques for deep learning, Pattern. Recognit. (2023) 109347.
[14] M. Deb, K.G. Dhal, A. Das, A.G. Hussien, L. Abualigah, A. Garai, A CNN-based model to count the leaves of rosette plants (LC-Net), Sci. Rep. 14 (1) (2024) 1496.
[15] X. Xia, C. Xu, B. Nan, Inception-v3 for flower classification, in: 2017 2nd international conference on image, vision and computing (ICIVC), IEEE, 2017, pp. 783–787.
[16] I.Z. Mukti, D. Biswas, Transfer learning based plant diseases detection using ResNet50, in: 2019 4th International conference on electrical information and communication technology (EICT), IEEE, 2019, pp. 1–6.
[17] V. Tiwari, R.C. Joshi, M.K. Dutta, Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images, Ecol. Inform. 63 (2021) 101289.
[18] S. Arya, R. Singh, A comparative study of CNN and AlexNet for detection of disease in potato and mango leaf, in: 2019 International conference on issues and challenges in intelligent computing techniques (ICICT), 1, IEEE, 2019, pp. 1–6.
[19] B. Sasmal, K.G. Dhal, A survey on the utilization of Superpixel image for clustering based image segmentation, Multimed. Tools. Appl. 82 (23) (2023) 35493–35555.
[20] B.A. Hassan, T.A. Rashid, Datasets on statistical analysis and performance evaluation of backtracking search optimisation algorithm compared with its counterpart algorithms, Data Brief 28 (2020) 105046.