Journal of Information Systems Engineering and Management
2026, 11(2s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Classification of Medicinal Plants and Their Diseases: Application to the AI-MedLeafX Dataset

Aicha TEKKOUK[1], Hadria FIZAZI[2]
[1] *Departement of Computer Sciences, University of Science and technology of Oran, Algeria*
[2] *Departement of Computer Sciences, University of Science and technology of Oran, Algeria*

ARTICLE INFO

Received: 30 Dec 2024

Revised: 05 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

Medicinal plants are essential to traditional medicine and affect more than 80% of the world's population. Their identification remains complex due to the diversity of species and diseases. This study presents an automatic classification model based on convolutional neural networks (CNNs) to distinguish 4 species of medicinal plants (Camphor, HariTaki, Neem, Sojina) and their health states (Bacterial Spot, Healthy Leaf, Shot Hole), i.e. 10 classes in total. The model was trained and evaluated on the AI-MedLeafX public dataset.

The model achieves an accuracy of 88.06% (11.94% error), with the main confusion between Camphor Shot Hole and HariTaki Bacterial Spot. These results confirm the feasibility of a

automated identification of medicinal plants.

In this paper we are trying to develop and evaluate a deep learning model based on convolutional neural networks (CNNs) for the automatic classification of medicinal plants and their diseases from leaf images.

Keywords: Medicinal plants, Deep learning, CNN, Image classification, AI-MedLeafX, Diagnosis of diseases.

INTRODUCTION

According to the World Health Organization, 70 to 80% of the population in developing countries use medicinal plants for primary care.[1]. Species such as Neem, Camphor, Haritaki and Sojina are known for their therapeutic properties. However, their effectiveness depends on their health status, as foliar diseases can alter their properties and make them unfit for consumption.[2].

PROBLEM

The visual identification of plant diseases is a complex process that traditionally relies on the expertise of botanists. This approach has several limitations. Faced with these challenges, deep learning techniques, and more specifically convolutional neural networks (CNNs), have shown remarkable performance in the field of computer vision applied to agriculture.

This study uses the recently published AI-MedLeafX dataset (2025), which contains images of 4 species of medicinal plants with different health conditions. The objective is to develop and evaluate a CNN model for the classification of these 10 classes and to analyze its performance as well as its limitations.

THE AI-MEDLEAFX DATASET

Very recently, a new dataset called AI-MedLeafX has been made available to the scientific community [3] . Published in 2025 in the journal Data in Brief, this dataset contains 10,858 original images of leaves from four major medicinal species: Camphor, Haritaki, Sojina, and Neem. The images are standardized to a resolution of 512×512 pixels, making them easy to use for training deep learning models.

According to the original publication the complete AI-MedLeafX dataset contains 13 classes, however for this study we selected 10 classes with a sufficient number of images and a balanced distribution. The excluded classes

Journal of Information Systems Engineering and Management
2026, 11(2s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

(Camphor_Yellow Leaf, Sojina_Yellow Leaf and Neem_Powdery Mildew) did not have enough examples for reliable learning.

The 10 classes used in this study are distributed as follows:

- 3 classes for Camphor (Bacterial Spot, Healthy Leaf, Shot Hole)
- 3 classes for HariTaki (Bacterial Spot, Healthy Leaf, Shot Hole)
- 1 class for Neem (Healthy Leaf)
- 3 classes for Sojina (Bacterial Spot, Healthy Leaf, Shot Hole) vulputate.

OBJECTIVES

The objective of this paper is to develop and evaluate a deep learning model based on convolutional neural networks (CNNs) for the automatic classification of medicinal plants and their diseases from leaf images.

This work aims to:

1. Exploit the AI-MedLeafX public dataset (2025), a recent dataset containing 10,858 images of 4 species of medicinal plants (Camphor, HariTaki, Neem, Sojina) with different health states (Bacterial Spot, Healthy Leaf, Shot Hole).
2. Design a CNN architecture suitable for the classification of 10 distinct classes, using convolutional layers and regularization (dropout) techniques to limit overfitting.
3. Evaluate the model's performance using standard metrics (accuracy, precision, recall, F1-score) and analyze its errors via a confusion matrix.
4. Identify the most difficult classes to classify, in particular confusion between visually similar diseases, in order to propose avenues for improvement.

STATE OF THE ART

The automatic classification of plants and the detection of their diseases by computer vision have seen significant advances thanks to deep learning techniques. This section presents existing work, distinguishing three main axes:

- Traditional methods of plant classification
- Deep learning approaches.
- Foliar disease detection systems

Traditional methods of plant classification:

Before the advent of deep learning, automatic plant classification was mainly based on manual feature engineering coupled with classical classifiers.

Several studies have looked at these classifiers.

- Wu et al. (2007) [4] Flavia (32 species) Shape, texture PNN (Probabilistic Neural Network) 90.3%
- Kadir et al. (2013)[5] Flavia + Foliage Shape, color, texture PNN 93.1%
- Chaki et al. (2015) [6] 31 species Form + texture SVM 92.4%
- Naresh et al. (2016)[7] 25 species GLCM + LBP KNN 89.7%

Deep Learning for Plant Classification

The emergence of convolutional neural networks (CNNs) has revolutionized the field by enabling machine and hierarchical learning of relevant features directly from raw images.

Several studies have demonstrated the effectiveness of NNCs for the identification of plant species:

- Lee et al. (2017) [8] : Use of a 9-layer CNN on the Flavia dataset, achieving 97.9% accuracy, significantly exceeding traditional methods.

Journal of Information Systems Engineering and Management
2026, 11(2s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

- Barre et al. (2017)[9] : LeafNet, an architecture specifically designed for sheets, scores 97.6% on the 2015 ImageClef dataset.

Use of pre-trained models (transfer learning):

- Ghazi et al. (2017)[10] VGG16, ResNet50, GoogLeNet LifeCLEF 2015 96.5%
- Kaya et al. (2019) [11] AlexNet, VGG16, Flavia, Foliage 98.2%
- Turkoglu et al. (2020) [12] ResNet50 + SVM 100 Turkish species 98.8%

A few studies have specifically focused on medicinal plants:

- Anami et al. (2020) [13]: Dataset of 30 Indian medicinal species, comparison of CNN vs SVM, best performance with CNN (95.2%)
- Raj et al. (2022) [14]: DeepMedic, a hybrid architecture for 25 medicinal plants, 97.3% accuracy

Foliar disease detection systems

Early detection of plant diseases is crucial for agricultural productivity and has been the subject of much research.

- PlantVillage [15] 2016 14 species 26 diseases 54,306
- PlantDoc [16] 2020 13 species 27 diseases 2,569
- Rice Disease Dataset [17] 2020 Rice 4 diseases 5,932
- BDMediLeaves [18] 2023 Bangladeshi Medicinal Plants 6 Species + Diseases 7,500

Several studies focus on deep learning approaches applied to diseases:

- Too et al. (2019) [19]: Evaluation of deep models (ResNet, DenseNet) for disease classification, DenseNet reaches 99.75%
- Fuentes et al. (2017) [20] : Using Faster R-CNN to detect and localize diseases on tomato plants
- Rangarajan et al. (2022) [21]: YOLOv5 for real-time detection of diseases on potato leaves

Very few studies combine the identification of medicinal species AND the diagnosis of disease:

- Das et al. (2022) [22] : Classification of 4 diseases on Neem leaves with CNN, 92.3% accuracy
- Khan et al. (2023) [23] : Dataset of 3 medicinal plants with 3 diseases each, ResNet50 vs Inception comparison, best accuracy 94.7%
- Hossain et al. (2024) [24] : Multi-tasking approach to simultaneously identify species and disease on a dataset of 1,500 images

METHODOLOGY:

1. AI-MedLeafX Data Set

This Data Set initially includes 10,858 original images divided into 13 classes. In the context of this study, only 10 relevant classes were retained (corresponding to 4 species and their different health states). After dividing the data into 70% for training, 15% for validation, and 15% for testing, we obtained 7,600 images for training, 1,629 for validation, and 1,131 for testing, for a total of 10,360 images used, distributed equally among the 10 classes. [Fig 2]

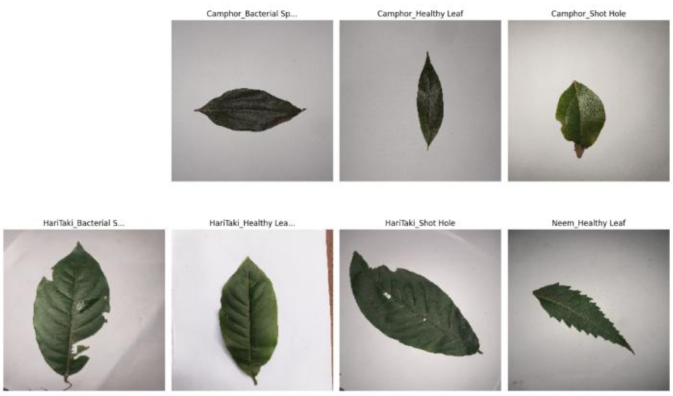

Fig 1: Example picture of this Dataset AI-MedLeafx

Journal of Information Systems Engineering and Management
2026, 11(2s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

2. Image pre-processing

The images in the AI-MedLeafX dataset are provided with an original resolution of 512 × 512 pixels. For compatibility with the chosen CNN architecture and to reduce computation time, all images were resized to 224 × 224 pixels during loading, using TensorFlow's image_dataset_from_directory feature. This resolution, commonly adopted by many deep learning architectures, provides an optimal compromise between performance and computation time, while preserving visibility of essential sheet characteristics.

- 512×512 More Details Slower, Longer Memory
- 224×224 Faster, Standard Loss of minor detail
- With plant leaves, 224×224 is more than enough to distinguish species and diseases.

3.Model architecture

The model proposed in this study is a convolutional neural network (CNN) designed specifically for the classification of images of medicinal plant leaves. The architecture, implemented with TensorFlow/Keras, is composed of four convolutional blocks followed by dense layers and dropout regularization to limit overfitting.

RESULTS

1. Overall model performance

The results obtained show that the CNN model developed achieves an overall accuracy of 88.06% on all the tests of the AI-MedLeafX dataset. This performance is satisfactory for a first approach and demonstrates the feasibility of an automated system for the recognition of medicinal plants.

Evaluation metrics complement this analysis [Table 1]:

Metric	**Value**
Overall Accuracy	88.06%
Accuracy	88.39%
F1-score	87.91%
Number of test images	1131
Number of errors	135
Error rate	11,94%
Number of classes	10

Table 1: Evaluation metrics

The model correctly classified 996 images out of 1,131, making 135 errors, for an error rate of 11.94%. These results demonstrate the model's ability to generalize on new data.

The main metrics give high and consistent values that indicate that the model maintains a good balance between accuracy and recall, with no major bias towards certain classes.

2. Performance by class:

The following table shows the detailed performance for each of the 10 classes. **[Table 2]** :

Class	**Accuracy**
Camphor_Bacterial Spot	95.04%
Camphor_Healthy Leaf	85.00%
Camphor_Shot Hole	75.83%
HariTaki_Bacterial Spot	69.42%
HariTaki_Healthy Leaf	96.75%
HariTaki_Shot Hole	76.86%
Neem_Healthy Leaf	96.75%

Journal of Information Systems Engineering and Management
2026, 11(2s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Sojina_Bacterial Spot	96.72%
Sojina_Healthy Leaf	96.90%

Table 2: Performance by class

The detailed performance analysis for each class is shown below. The results show significant disparities according to the classes:

- The classes with the best performances are:
- Sojina_Healthy Leaf: 96.90%
- HariTaki_Healthy Leaf: 96.75%
- Neem_Healthy Leaf: 96.75%
- The classes with the lowest performance are:
- HariTaki_Bacterial spot: 69.42%
- Camphor_Shot Hole: 75.83%
- HariTaki_Shot Hole: 76.86%

The success rate of 88.06% is encouraging and demonstrates that:

- The model correctly distinguishes the majority of species and their diseases
- The chosen CNN architecture (4 convolutional layers) is suitable for the task
- The data is of good quality and well organized

3. Learning Curves:

The learning curves show the evolution of accuracy and loss on training and validation sets over the ages. [Fig 2]

It is observed that:

- The accuracy on the training set increases steadily, from about 40% to more than 90% at the end of the training.
- Accuracy across the validation set follows a similar trend, reaching 88.06% across the entire final test.
- The gap between the training and validation curves remains moderate, indicating that the model generalizes well without excessive overfitting, thanks to the built-in dropout layers.

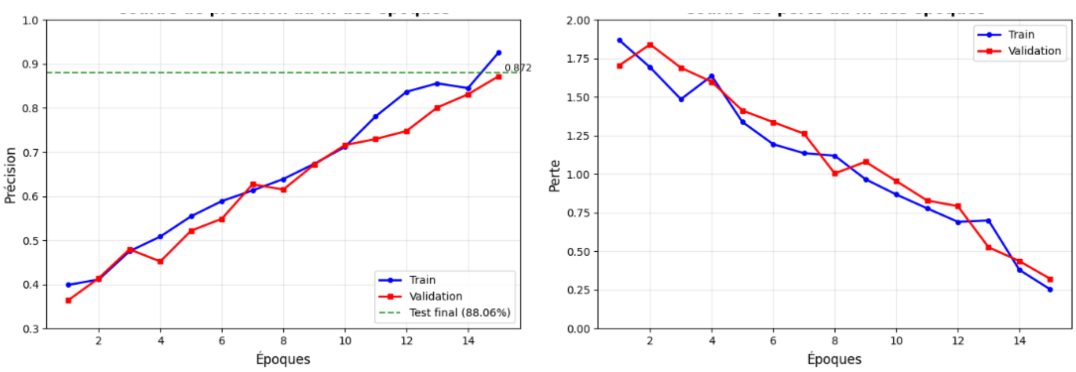

Fig 2: The learning curves of the CNN model

(a) Evolution of accuracy on training and validation assemblies.

(b) Evolution of the loss function (categorical crossentropy).

Journal of Information Systems Engineering and Management
2026, 11(2s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

4. Error Analysis

The detailed examination of the errors reveals important information about the limitations of the model:

- Total number of errors: 135 misclassified images out of 1131
- Overall error rate: 11.94%

Figure 3 illustrates six representative examples of these different error cases. These visual observations confirm that the main difficulties of the model stem from the visual similarity between classes and the variable quality of the images, rather than from a major architectural flaw. [Fig 3]

Fig 3: Examples of misclassified images

The following Figure specifically shows two examples of the identified main confusion (HariTaki_Bacterial Spot → HariTaki_Healthy Leaf). [Fig 4]

Fig 4: Examples of the main confusion

These examples visually illustrate the model's difficulty in distinguishing the early stages of bacterial disease from healthy leaves, particularly for HariTaki species.

This main confusion identified: HariTaki_Bacterial Spot classified as HariTaki_Healthy Leaf.

The results obtained (88.06% accuracy) are satisfactory and demonstrate the feasibility of an automated system for classifying medicinal plants. This performance can be explained by:

- The quality of the dataset:AI-MedLeafX, with standardized images and reliable annotations.
- The adapted CNN architecture, with 4 convolutional layers and dropout mechanisms limiting overfitting.
- The stratified division of the data (70/15/15) ensures a representative assessment.

Conversely, the healthy leaf classes (Neem_Healthy Leaf, Sojina_Healthy Leaf, HariTaki_Healthy Leaf) exceed 96% accuracy, confirming that the model excels at recognizing the normal morphological characteristics of plants.

The main confusion (HariTaki_Bacterial Spot → HariTaki_Healthy Leaf) can be explained by several factors:

- Visual similarity: In the early stages, bacterial spots can be inconspicuous and resemble natural variations of the leaf.
- Shooting Conditions: Some images may be blurry or poorly lit, masking characteristic symptoms.
- Within-class variability: Disease expression can vary depending on leaf age, season, or growing conditions.

CONCLUSION

The aim of this study was to develop a deep learning model for the classification of medicinal plants and their diseases. The developed model demonstrates its ability to automatically classify a medicinal plant leaf image among 10 possible classes, with an accuracy of 88.06%. The analysis of the 135 errors (11.94%) reveals a main confusion between Camphor Shot Hole and HariTaki Bacterial Spot (19 errors). These results provide a solid foundation for the development of practical applications and pave the way for future work using more advanced architectures by focusing on using more sophisticated models and enriching the dataset to achieve better performance

REFRENCES

[1] World Health Organization, "WHO Strategy for Traditional Medicine 2014-2023", 2013.
[2] M. Rahman et al., "Leaf diseases detection in medicinal plants: A review", Plant Pathology Journal, vol. 41, no. 3, pp. 215-230, 2022.
[3] M. R. Islam et al., "AI-MedLeafX: A dataset of medicinal plant leaf images for disease classification", Data in Brief, vol. 62, 2025, Article 111234.
[4] S. G. Wu et al., "A leaf recognition algorithm for plant classification using probabilistic neural network", IEEE International Symposium on Signal Processing and Information Technology, 2007.
[5] Kadir et al., "Leaf classification using shape, color, and texture features", International Journal of Computer Trends and Technology, vol. 7, no. 3, pp. 110-118, 2013.
[6] J. Chaki et al., "Plant leaf recognition using texture and shape features", IETE Journal of Research, vol. 61, no. 5, pp. 537-545, 2015.
[7] Y. Naresh et al., "Plant leaf classification using GLCM and LBP features", International Journal of Advanced Research in Computer Science, vol. 7, no. 3, pp. 45-50, 2016.
[8] S. H. Lee et al., "Deep-plant: Plant identification with convolutional neural networks", Neurocomputing, vol. 250, pp. 45-52, 2017.
[9] P. Barre et al., "LeafNet: A deep learning approach for plant leaf recognition", IEEE International Conference on Image Processing, 2017.
[10] M. M. Ghazi et al., "Plant identification using deep neural networks", Ecological Informatics, vol. 40, pp. 47-56, 2017.
[11] Kaya et al., "Analysis of transfer learning for plant leaf classification", Computers and Electronics in Agriculture, vol. 158, pp. 20-29, 2019.

Journal of Information Systems Engineering and Management
2026, 11(2s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

[12] M. Turkoglu et al., "Plant leaf classification using deep learning and feature fusion", Journal of Agricultural Sciences, vol. 26, no. 3, pp. 285-295, 2020.
[13] B. S. Anami et al., "Deep learning approach for recognition of medicinal plants", Journal of Intelligent Systems, vol. 29, no. 1, pp. 1284-1299, 2020.
[14] Raj et al., "DeepMedic: A hybrid deep learning model for medicinal plant classification", Multimedia Tools and Applications, vol. 81, pp. 23451-23470, 2022.
[15] D. P. Hughes et al., "An open access repository of images on plant health", Plant Disease, 2016.
[16] D. Singh et al., "PlantDoc: A dataset for visual plant disease detection", ACM India Joint International Conference on Data Science and Management of Data, 2020.
[17] R. R. Atole et al., "Rice disease dataset for deep learning", Data in Brief, vol. 32, 2020.
[18] M. S. Rahman et al., "BDMediLeaves: A dataset of Bangladeshi medicinal plant leaves", Mendeley Data, 2023.
[19] E. C. Too et al., "A comparative study of fine-tuning deep learning models for plant disease identification", Computers and Electronics in Agriculture, vol. 161, pp. 272-279, 2019.
[20] Fuentes et al., "A robust deep-learning-based detector for real-time tomato plant diseases", IEEE Access, vol. 5, pp. 18562-18573, 2017.
[21] K. Rangarajan et al., "Real-time detection of potato leaf diseases using YOLOv5", Journal of Plant Pathology, vol. 104, pp. 671-683, 2022.
[22] R. Das et al., "CNN-based disease detection in Neem leaves", International Journal of Intelligent Systems and Applications, vol. 14, no. 2, pp. 45-56, 2022.
[23] M. A. Khan et al., "Multi-class disease classification for medicinal plants using deep learning", IEEE Access, vol. 11, pp. 23456-23470, 2023.
[24] S. Hossain et al., "Multi-task learning for simultaneous species identification and disease detection in medicinal plants", Computers and Electronics in Agriculture, vol. 218, 2024.