Indonesian Journal of Electrical Engineering and Computer Science
Vol. 39, No. 3, September 2025, pp. 1587~1594
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v39.i3.pp1587-1594

A comparative study of CNN architectures for the detection of tomato leaf diseases

Soumia Benkrama, Benyamina Ahmed, Nour El Houda Hemdani
Department of Computer Science, Faculty of Exact Sciences, Tahri Mohammed University, Bechar, Algeria

Article Info

Article history:

Received Jun 20, 2024
Revised Apr 15, 2025
Accepted Jul 3, 2025

Keywords:

Convolutional neural networks
Deep learning
EfficientNetB1
Precision agriculture
ResNet
VGG

ABSTRACT

Recent advancements in computer vision and machine learning (ML) have revolutionised various sectors, including precision agriculture (PA). In our study, we focused on detecting tomato leaf diseases (TLD) using deep learning (DL) techniques. Using a convolutional neural network (CNN) model, we developed an agricultural image index to accurately detect TLD. By utilizing available datasets from Kaggle, we trained our model to recognize various TLDs. To determine the most effective one, we compared multiple architectures, including VGG, ResNet, and EfficientNetB1. The obtained results demonstrated a classification accuracy of over 99% on the test set. This approach has allowed us to accelerate and enhance the disease detection process, positively impacting agricultural communities by reducing crop losses and enabling early intervention in case of disease outbreaks. Our study highlights the effectiveness of CNN models in the detection of TLD, paving the way for future applications in PA.

Corresponding Author:

Soumia Benkrama
Department of Computer Sciences, Faculty of Exact Sciences, Tahri Mohammed University
Independence Road B.P 417, Bechar 08000, Algeria
Email: benkrama.soumia@univ-bechar.dz

1. INTRODUCTION

Agriculture is one of the oldest and most essential professions worldwide, playing a crucial role in the economy. The integration of AI technologies in agriculture has led to significant advancements, including healthier crop production [1]-[3], pest control [4], [5], soil and growth condition monitoring, and crop management [6] and [7]. These technologies also reduce workload and enhance efficiency across the entire food supply chain.

In recent years, precision agriculture (PA) has increasingly incorporated computing fields such as image processing (IP) and deep learning (DL). DL, a subset of AI derived from ML, enables machines to learn autonomously by constructing data representations during training. Convolutional neural network (CNNs), commonly used in IP, are designed for pixel-based analysis and leverage DL for both descriptive and generative tasks.

Although tomatoes are among the most widely cultivated vegetables globally, they are especially susceptible to a range of diseases, particularly foliar infections. Early detection of these diseases is essential to prevent their spread and maximize healthy tomato production [8]. This research aims to establish a system that automates the detection of foliar diseases, enabling the identification and classification of infections at their early onset. Implementing CNNs can significantly enhance detection accuracy, improve performance, and provide faster response times, ultimately benefiting farmers.

The paper presents the following key contributions:

– Develop a computerized framework for detecting tomato leaf diseases (TLD) and exploring various detection methods.

- Application of advanced neural networks to model data patterns effectively.
- Analysis and discussion of results obtained from multiple datasets using different CNN architectures for TLD detection and identification.

2. RELATED WORK

Agriculture faces a major global problem with uncontrolled epidemics, often leading to significant economic losses. Consequently, much research in plant epidemiology has focused on the possibility of predicting the emergence of plant diseases, particularly in tomatoes, through various tests [9]-[12]. Tomatoes are among the most important agricultural products in the world, has an annual production of tens of millions of tons. However, tomato plants are frequently afflicted by foliar diseases that lower their production, including late blight, leaf mold, mosaic virus, Septoria leaf spot, spider mite, target spot, and leaf yellows virus. Many studies have been carried out to combat these illnesses and boost tomato output [13], [14]. Technological innovations hold great potential for detecting and controlling diseases, and DL methods have also demonstrated their effectiveness in many fields, especially agriculture. These findings are highly promising and imply that programs that assist farmers and plant pathologists in promptly and precisely identifying and managing diseases may be created [15]. Such applications could reduce the economic losses associated with tomato foliar diseases and increase the production of this essential agricultural product.

According to Mim *et al.* [16] four CNN architectures—VGG-16, VGG-19, ResNet, and Inception V3—were taken into consideration for the categorization and identification of TLD utilizing CNN approaches. Extractive analysis and parameter adjustment were used to identify and classify TLD. Self-collected field data and a laboratory dataset were also used. Ahmad *et al.* [16] found that, on laboratory datasets, all architectures outperformed field data, with performance variations ranging from 10% to 15% for various parameters. The method that performed the best on both datasets was found to be Inception V3.

Mim *et al.* [17] focused on developing a system using artificial intelligence and CNN techniques to diagnose diseases affecting tomato plants. A digital camera was used to take pictures of a healthy plant sample and samples of leaves afflicted by five distinct tomato illnesses. CNN was then used to evaluate the photos and categorize them according to various diseases and healthy patterns. After evaluation, the system's total accuracy was determined to be 96.55%. To assess the system's usefulness, it was also put to the test in actual field settings in agricultural settings. The system was able to accurately identify diseases and give farmers practical advice on how to handle crop issues.

Hlaing and Zaw [18] using a stationary wavelet transform for texture characteristics and explicit extraction functions in the form of statistical features, Hlaing and Zaw proposed a method that separates the leaf image from the backdrop. A support vector machine (SVM) classifier receives these characteristics and uses them to distinguish between seven input categories—six illnesses and one healthy. Ten categories (nine illnesses and one healthy) were classified for tomato leaf photos using four deep learning (DL) models: LeNet, VGG16, ResNet, and Xception. VGG16 achieved a maximum accuracy of 99.25%. Tm *et al.* [19] employed AlexNet, GoogleNet, and LeNet models to tackle the same classification problem, achieving 94-95% accuracy.

Threshold-based segmentation was suggested by Annabelle and Muthulakshmi [20] to recognize and separate impacted areas from the leaf image. They employed the Random Forest classifier to categorize three diseases and healthy leaves, achieving a 94.1% accuracy rate after extracting various features, including difference, homogeneity, and contrast. Agarwal *et al.* [21] modified the VGG16 architecture to create a bespoke CNN model. They evaluated the accuracy of this model, which was 98.4% in classifying ten categories, by comparing it with three DL models (e.g. VGG16, InceptionV3, and MobileNet) and conventional machine learning (ML) models (e.g., random forests and decision trees). Three paradigms were utilized by Ouhami *et al.* [22] VGG16, DenseNet-161, and DenseNet-121. With a 95.65% accuracy rate, DenseNet-161 produced the best results.

Similarly, Ali *et al.* [23] showed a greater accuracy of 99.8% using InceptionV3. Nevertheless, these excellent outcomes were attained using photographs of plants enhanced by deep object identification techniques used to identify leaf diseases. Liu and Wuang [24] reported an average accuracy of 92.5% when using the YOLOv3 algorithm to detect gray spot illness.

Although various techniques for detecting TLD exist, previous work suffers from several shortcomings:

- First, by adding small image changes, some research expands the dataset size. DL models, however, are typically resistant to these slight modifications. By enabling the model to identify the original photos instead of concentrating on the true attributes, this duplication can artificially enhance outcomes.
- Second, there are hazards associated with overfitting, hardware requirements, reliability, and efficiency while creating a custom CNN model. With thousands of applications built on top of these models, deep transfer learning with pre-existing network architectures offers intrinsic credibility.

Automatic identification and detection of different types of TLD remain crucial. Therefore, this work focuses on detecting tomato foliar diseases using several DL architectures.

3. PROPOSED APPROACH

This study aims to develop an automated image detection system for expert-level tasks, reducing human effort and cost. Focusing on DL, particularly CNNs, the research compares different CNN architectures for TLD classification and diagnosis. Five experiments were conducted:
Experiment 1: Using the EfficientNetB1 architecture without applying any additional filters.
Experiment 2: Using the EfficientNetB1 architecture with the application of preprocessing.
Experiment 3: Using the EfficientNetB1 architecture with the application of Gaussian Blur as part of image preprocessing.
Experiment 4: Using the ResNet-50 architecture for the analysis and detection of images related to TLD.
Experiment 5: Using the VGG-19 architecture for the analysis and detection of images related to TLD.

To identify the most successful strategy, the study assesses these predictions. Figure 1 illustrates the overall architecture of the proposed model. It represents the complete pipeline for detecting tomato leaf disease (TLD) using a CNN-based deep learning approach.

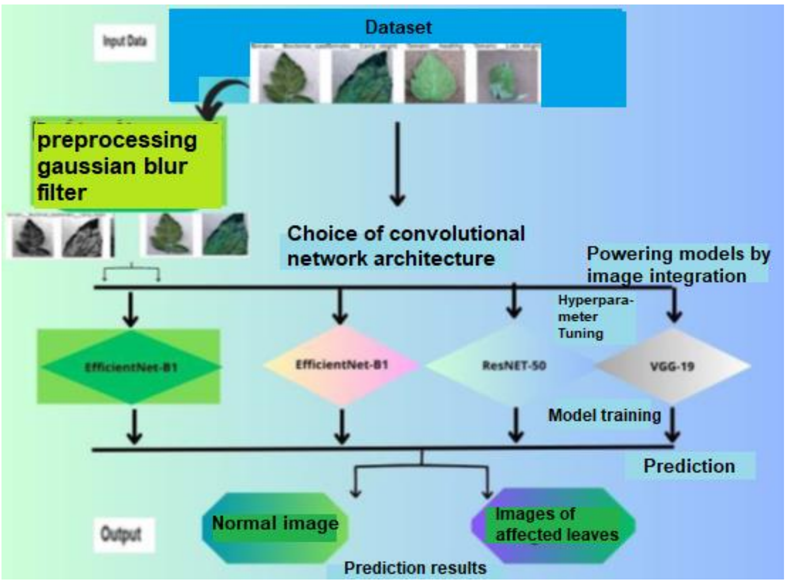


Figure 1. The general architecture of the proposed model

The system detects TLD using multiple CNN architectures on a dataset with ten classes—nine for diseases and one for healthy plants. It operates in two main phases.

3.1. Training phase

In the training phase, a CNN extracts features from images of nine TLD categories and healthy plants using 80% of the data. Convolutional layers detect patterns, pooling layers reduce dimensionality, and fully connected layers classify accurately. This approach optimizes model parameters for high-precision predictions.

3.2. Test phase (prediction)

In the testing phase, the remaining 20% of data evaluates the CNN model's ability to generalize and predict TLD accurately. Model predictions are compared to actual labels using metrics like precision, recall, and F-measure. This step assesses performance across all classes and identifies areas for improvement to optimize accuracy.

Our database includes ten categories of TLD and healthy plants:

- Tomato bacterial spot: dark spots on leaves and fruit, causing plant deterioration.
- Tomato early blight: circular brown spots on lower leaves, affecting growth and harvest.
- Tomato late blight: leads to leaf and fruit rot, potentially causing major crop losses.

- Tomato leaf mold: yellow spots and leaf deformation, impacting plant respiration and nutrition.
- Tomato septoria leaf spot: small circular spots on lower leaves, reducing yield quality and quantity.
- Tomato spider mites (two-spotted spider mite): Yellow spots on leaves and sticky residue on fruit, potentially severe if uncontrolled.
- Tomato target spot: round spots with concentric circles on leaves, affecting plant health.
- Tomato yellow leaf curl virus: causes leaf and fruit deformation, leading to plant dwarfism and reduced yield.
- Tomato mosaic virus: leaf deformations and yellowing, impacting plant growth and productivity.
- Tomato healthy: represents plants free from diseases or infestations.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

The efficiency of several models for TLD diagnosis and classification is assessed in this paper. By comparing the results, researchers and farmers can identify the most accurate model, enhancing disease detection and control.

4.1. Dataset

The project uses a Kaggle database containing nine TLD categories and one for healthy plants (Kaggle dataset). This dataset is an excellent resource for analyzing TLD, improving farming methods, and forecasting the development of disease. Table 1 provides details about the dataset.

Table 1. Tomato leaves dataset

Dataset	Training	Testing	Total
Tomato_mosaic_virus	1000	100	1100
Target_Spot	1000	100	1100
Bacterial_spot	1000	100	1100
Tomato_Yellow_Leaf_Curl_Virus	1000	100	1100
Late_blight	1000	100	1100
Leaf_Mold	1000	100	1100
Early_blight	1000	100	1100
Spider_mites Two-spotted_spider_mite	1000	100	1100
Septoria_leaf_spot	1000	100	1100
Tomato_healthy	1000	100	1100
Total	1000	100	1100

4.2. Evaluation metrics used

An ML model's performance and efficacy in classification or prediction tasks are measured using evaluation metrics. This study measured accuracy and reliability using a variety of evaluation indicators [25]. The proposed model's performance was tested and validated. Accuracy, precision, recall, and F1-score were determined using true positives (TPos), true negatives (TNeg), false positives (FPos), and false negatives (FNeg). Each measure has a mathematical definition [25]:

$$Accuracy = \frac{TPos+TNeg}{TPos+TNeg+FPos+FNeg} \tag{1}$$

$$Precision = \frac{TPos}{TPos+FPos} \tag{2}$$

$$Recall = \frac{TPpos}{TPos+FNeg} \tag{3}$$

$$f1-score = 2 \times \frac{recall \times precision}{recall+prcision} \tag{4}$$

4.3. Experimental test and results

Five experiments were conducted, with the first three using the EfficientNetB1 architecture for TLD classification. The model's performance was evaluated and compared across these experiments, demonstrating that EfficientNetB1 is an excellent choice based on the impressive results obtained [26]:
Experiment 1: EfficientNetB1 without additional filters.
Experiment 2: EfficientNetB1 with preprocessing applied before modeling.
Experiment 3: EfficientNetB1 with Gaussian Blur as the preprocessing technique.

Table 2 shows the performance of the EfficientNetB1 model before preprocessing, with Gaussian Blur filtering, and without filtering.

Table 2. Comparison of accuracy based on the number of epochs for the tomato leaf dataset

Epochs	EfficientNetB1		
	EfficientNeB1 without filtre	With Filtre Gaussian Blur	With preprocessing
	Accuracy		
05	0.976	0.9	0.891
10	0.995	0.961	0.938
15	0.995	0.986	0.933
20	0.995	0.991	0.933
Accuracy Score	0.990	0.991	0.937
Total time	**564 mins**	**346 mins**	368 mins
	9.4H	**5.76 H**	6.13H
Total size	27.1 MB	27.1 MB	27.1 MB

Despite good results with the Gaussian Blur filter, EfficientNetB1 was chosen as the best option due to its high performance (99% success rate) and robustness to transformations. While Gaussian Blur achieved slightly better results in less time, EfficientNetB1 excelled in accurate classification. Experiment 4 explored the ResNet-50 architecture for TLD analysis and classification, with results shown in Figure 2.

	precision	recall	f1-score
0	0.985	0.971	0.978
1	0.964	0.972	0.968
2	1.000	1.000	1.000
3	0.995	0.973	0.984
4	1.000	0.987	0.993
5	0.991	0.978	0.985
6	0.960	0.986	0.973
7	0.979	0.970	0.974
8	0.980	1.000	0.990
9	0.973	0.991	0.982
accuracy			0.983
macro avg	0.983	0.983	0.983
weighted avg	0.983	0.983	0.983

Figure 2. Results of TLD detection evaluation parameters based on ResNet-50 architecture

ResNet-50 demonstrated excellent performance in TLD detection, achieving 98.3% overall accuracy and 100% classification accuracy for some classes, with high recall and F1 score. Despite an 8.13-hour training time and a 94.9 MB model size, it remains a reliable choice for precise and rapid detection. Experiment 5 explored the VGG-19 architecture for TLD analysis and classification, with results shown in Figure 3.

	precision	recall	f1-score
0	0.92	0.90	0.91
1	0.75	0.85	0.80
2	1.00	0.97	0.98
3	0.89	0.83	0.86
4	0.87	0.87	0.87
5	0.87	0.81	0.83
6	0.85	0.83	0.84
7	0.80	0.87	0.84
8	0.97	0.97	0.97
9	0.95	0.94	0.94
accuracy			0.88
macro avg	0.89	0.88	0.88
weighted avg	0.88	0.88	0.88

Figure 3. Results of TLD detection evaluation parameters based on VGG-19 architecture

VGG-19 achieved 88% overall and 100% classification accuracy for some categories, demonstrating high precision and recall in TLD detection. Despite an 8.26-hour training time and a 1.52 GB model size, it remains a powerful and reliable choice for accurate detection. Table 3 presents a comparison of the EfficientNetB1, ResNet-50, and VGG-19 architectures in TLD detection.

Table 3. Comparison between EfficientNetB1, ResNet-50, and VGG-19 architectures

Epochs	Architecture		
	EfficientNetB1	Resnet-50	VGG-19
05	0.957	0.835	0.859
10	0.995	0.975	0.761
15	0.995	0.982	0.897
20	0.995	0.988	0.9
Accuracy Score	**0.99**	**0.983**	0.882
Total time	**564 minutes**	**488 minutes**	496 minutes
	9.4H	**8.13H**	8.26H
Model size	27.1 MB	94.9 MB	1.52 GB

Based on Table 4, EfficientNetB1 is the best model for TLD detection, offering high accuracy, recall, and overall balance, along with reasonable training time and optimal model size. ResNet-50 also performs well but requires longer training time and has a larger model size. VGG-19, while providing acceptable results, is outperformed by both EfficientNetB1 and ResNet-50.

Due to its exceptional efficiency and performance, EfficientNetB1 is the ideal option. Accuracy, recall, precision, F1-score, and size are the metrics used to evaluate the model; the results are shown in Table 4 for epoch 20 with a learning rate of 0.000001.

Table 4. Summary of all results for Epoch=20

Model	Accuracy %	Precision %	Recall %	F1-score %	Model size
EfficientNetB1	**0.996**	**0.99**	**1.00**	**0.99**	**27.1 MB**
Resnet-50	0.986	0.97	0.99	0.98	94.9 MB
VGG-19	0.9	0.95	0.94	0.94	1.52 GB

5. CONCLUSION

EfficientNetB1, ResNet-50, and VGG-19 CNN architectures were compared in order to detect tomato foliar diseases, which are a major threat to crop yields and can result in large financial losses. Five experiments were carried out, including tests with EfficientNetB1 without filters, preprocessing steps, and Gaussian blur, as well as evaluations using ResNet-50 and VGG-19. The results proved that EfficientNetB1 was the most successful model for TLD classification, achieving the best performance with great precision. By combining EfficientNetB1 with PA, farmers can efficiently evaluate crop health and make accurate choices about managing diseases. To increase diagnostic performance and accuracy, future research should concentrate on growing the dataset, creating a mobile application for real-time disease warnings, and improving the neural network model.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Soumia Benkrama	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Ahmed Benyamina		✓				✓		✓	✓	✓	✓	✓		
Nour El Houda Hemdani	✓		✓	✓		✓			✓		✓		✓	

C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding acquisition
Fo	: **Fo**rmal analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, Soumia Benkrama, upon reasonable request.

REFERENCES

[1] B. Mondal, M. Rana, M. Bhushan, A. Negi, I. Dawar, and S. Layek, "Crop Disease Prediction using Machine Learning and Deep Learning: An Exploratory Study," *International Conference on Sustainable Computing and Smart Systems, ICSCSS 2023 - Proceedings*, pp. 278–283, 2023, doi: 10.1109/ICSCSS57650.2023.10169612.

[2] M. Manju, P. Indira Priya, S. Shivaraj, P. Rissi Kumar, and P. R. Shivesh, "Smart Fields: Enhancing Agriculture with Machine Learning," *2nd International Conference on Artificial Intelligence and Machine Learning Applications: Healthcare and Internet of Things, AIMLA 2024*, 2024, doi: 10.1109/AIMLA59606.2024.10531419.

[3] V. Bajait and N. Malarvizhi, "Recognition of suitable Pest for Crops using Image Processing and Deep Learning Techniques," *Proceedings - 2022 4th International Conference on Advances in Computing, Communication Control and Networking, ICAC3N 2022*, pp. 1042–1046, 2022, doi: 10.1109/ICAC3N56670.2022.10074225.

[4] D. Devi, S. R. Devakadacham, D. Saveetha, and J. Manikandan, "Enhancing Insect Species Identification in Agriculture using Fusion BiLSTM Network and VGG-16 CNN Architecture," *2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, pp. 1–6, May 2024, doi: 10.1109/ACCAI61061.2024.10602372.

[5] B. Fulkar, S. Mendhe, and P. Patil, "Artificial Intelligence Cultivation: Transforming Agriculture for a Smart and Sustainable Future," *2nd International Conference on Intelligent Data Communication Technologies and Internet of Things, IDCIoT 2024*, pp. 960–964, 2024, doi: 10.1109/IDCIOT59759.2024.10467857.

[6] M. R. Mahmood, M. A. Matin, S. K. Goudos, and G. Karagiannidis, "Machine Learning for Smart Agriculture: A Comprehensive Survey," *IEEE Transactions on Artificial Intelligence*, Jun. 2023, doi: 10.1109/TAI.2023.3345278.

[7] R. Mahakud, B. K. Pattanayak, and B. Pati, "Internet of things and multi-class deep feature-fusion based classification of tomato leaf disease," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 25, no. 2, pp. 995–1002, 2022, doi: 10.11591/ijeecs.v25.i2.pp995-1002.

[8] A. Sofiane, B. Mostefa, and B. Soumia, "Deep Learning Model Based on VGG16 for Tomato Leaf Diseases Detection and Categorization," *2024 2nd International Conference on Electrical Engineering and Automatic Control, ICEEAC 2024*, 2024, doi: 10.1109/ICEEAC61226.2024.10576347.

[9] Y. Wang, P. Zhang, and S. Tian, "Tomato leaf disease detection based on attention mechanism and multi-scale feature fusion," *Frontiers in Plant Science*, vol. 15, p. 1382802, Apr. 2024, doi: 10.3389/FPLS.2024.1382802/BIBTEX.

[10] V. Cheemaladinne and S. R. K., "Tomato leaf disease detection and management using VARMAx-CNN-GAN integration," *Journal of King Saud University - Science*, vol. 36, no. 8, p. 103340, Sep. 2024, doi: 10.1016/J.JKSUS.2024.103340.

[11] L. J, S. S, S. D, and N. Thomas, "Tomato Leaf Disease Detection using Machine Learning Model," Mar. 2024, doi: 10.4108/EAI.23-11-2023.2343189.

[12] A. Gatla *et al.*, "Optimizing Edge AI for Tomato Leaf Disease Identification," *Engineering, Technology & Applied Science Research*, vol. 14, no. 4, pp. 16061–16068, Aug. 2024, doi: 10.48084/ETASR.7802.

[13] Z. Chen, G. Wang, T. Lv, and X. Zhang, "Using a Hybrid Convolutional Neural Network with a Transformer Model for Tomato Leaf Disease Detection," *Agronomy 2024, Vol. 14, Page 673*, vol. 14, no. 4, p. 673, Mar. 2024, doi: 10.3390/AGRONOMY14040673.

[14] M. Ferdouse Ahmed Foysal, M. Shakirul Islam, S. Abujar, and S. Akhter Hossain, *A Novel Approach for Tomato Diseases Classification Based on Deep Convolutional Neural Networks*, no. July. Springer Singapore, 2020.

[15] I. Ahmad, M. Hamid, S. Yousaf, S. T. Shah, and M. O. Ahmad, "Optimizing pretrained convolutional neural networks for tomato leaf disease detection," *Complexity*, vol. 2020, 2020, doi: 10.1155/2020/8812019.

[16] T. T. Mim, M. H. Sheikh, R. A. Shampa, M. S. Reza, and M. S. Islam, "Leaves Diseases Detection of Tomato Using Image Processing," *Proceedings of the 2019 8th International Conference on System Modeling and Advancement in Research Trends, SMART 2019*, pp. 244–249, Feb. 2020, doi: 10.1109/SMART46866.2019.9117437.

[17] C. S. Hlaing and S. M. M. Zaw, "Model-based statistical features for mobile phone image of tomato plant disease classification," *Parallel and Distributed Computing, Applications and Technologies, PDCAT Proceedings*, vol. 2017-Decem, pp. 223–229, Jul. 2017, doi: 10.1109/PDCAT.2017.00044.

[18] P. Tm, A. Pranathi, K. Saiashritha, N. B. Chittaragi, and S. G. Koolagudi, "Tomato leaf disease detection using convolutional neural networks," Aug. 2018, doi: 10.1109/IC3.2018.8530532.

[19] L. S. P. Annabel and V. Muthulakshmi, "AI-Powered Image-Based Tomato Leaf Disease Detection," *Proceedings of the 3rd International Conference on I-SMAC IoT in Social, Mobile, Analytics and Cloud, I-SMAC 2019*, pp. 506–511, Dec. 2019, doi: 10.1109/I-SMAC47947.2019.9032621.

[20] M. Agarwal, S. K. Gupta, and K. K. Biswas, "Development of Efficient CNN model for Tomato crop disease identification," *Sustainable Computing: Informatics and Systems*, vol. 28, p. 100407, Dec. 2020, doi: 10.1016/J.SUSCOM.2020.100407.

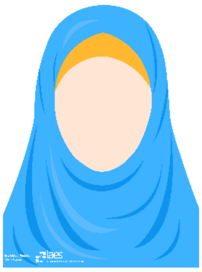
[21] M. Ouhami, Y. Es-Saady, M. El Hajji, A. Hafiane, R. Canals, and M. El Yassa, "Deep Transfer Learning Models for Tomato Disease Detection," *Image and Signal Processing*, vol. 12119, p. 65, 2020, doi: 10.1007/978-3-030-51935-3_7.

[22] A. Alhaj Ali, B. Chramcov, R. Jasek, R. Katta, S. Krayem, and E. Awwama, “Tomato Leaf Diseases Detection Using Deep Learning,” *Lecture Notes in Networks and Systems*, vol. 231 LNNS, pp. 199–208, 2021, doi: 10.1007/978-3-030-90321-3_18.
[23] J. Liu and X. Wang, “Early recognition of tomato gray leaf spot disease based on MobileNetv2-YOLOv3 model,” *Plant Methods*, vol. 16, no. 1, pp. 1–16, Jun. 2020, doi: 10.1186/S13007-020-00624-2/FIGURES/6.
[24] S. Benkrama and N. E. H. Hemdani, “Deep Learning with EfficientNetB1 for detecting brain tumors in MRI images,” *2023 International Conference on Advances in Electronics, Control and Communication Systems, ICAECCS 2023*, 2023, doi: 10.1109/ICAECCS56710.2023.10104761.
[25] T. Srivastava, “Important model evaluation metrics for machine learning everyone should know,“ C*ommonly Used Machine Learning Algorithms: Data Science*, 2020.
[26] S. Benkrama and N. E. H. Hemdani, “Deep Learning with EfficientNetB1 for detecting brain tumors in MRI images,” *2023 International Conference on Advanced Electronics, Control and Communication Systems*, *ICAECCS 2023*, 2023, doi: 10.1109/ICAECCS56710.2023.10104761

BIOGRAPHIES OF AUTHORS

Soumia Benkrama is currently an Associate Professor at the Faculty of Exact Sciences, Computer Science Department, University Tahri Mohamed-Béchar, Algeria. She received a master's and Ph.D. degrees in Computer Science at the University of Science and Technology Mohamed Boudiaf, Oran, Algeria. Her research areas are image processing, machine learning, pattern recognition, and computational intelligence. She can be contacted at email: benkrama.soumia@univ-bechar.dz.

Ahmed Benyamina Lecturer at the Faculty of Exact Sciences, Computer Science Department, University Tahri Mohamed-Béchar, Algeria. Dr. Benyamina holds a Doctor of Computer Science from the University of Science and Technology Mohamed Boudiaf, Oran, Algeria. His research areas encompass data analysis, algorithmics and complexity, image processing, machine learning, pattern recognition computational intelligence, and speech recognition. In addition to his lecturing responsibilities, Dr. Benyamina serves as the Head of the Master's specialization in Artificial Intelligence. He can be contacted at email: benyaminaa@gmail.com.



Nour El Houda Hemdani was born in Bechar in 1999. She had her baccalaureate in 2017. She studied computer science at the University of Tahri Mohammed in Bechar. She received a license diploma in 2020 and a master's in artificial intelligence in 2023. Her research interests are machine learning (deep learning), image processing, and computer vision. She can be contacted at email: hamhouda7@gmail.com.