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Enhancing the identification of date palm diseases with ensemble learning techniques

Mohammed El Amin Kourtiche[1,3], Ikram Kourtiche[1,3], Ahmed Bouida[2,3]
[1]Department of Mathematics and Computer Science, Faculty of Exact Sciences, Tahri Mohamed University, Bechar, Algeria
[2]Department of Material Sciences, Faculty of Exact Sciences, Tahri Mohamed University, Bechar, Algeria
[3]Laboratory of Information Processing and Telecommunication (LTIT), Tahri Mohamed University, Bechar, Algeria

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ABSTRACT

Date palms (*Phoenix dactylifera L.*) are one of the most important crops in the arid and semi-arid regions, providing food, shelter, and economic benefits. However, plant disease identification is an important challenge in the agriculture sector and it is critical to mitigating crop loss and disease spread. Early detection of palm diseases is at the core of our study. In this work, we identify and classify three nutrient deficiencies and five diseases using a set of convolutional neural network (CNN) architectures (VGG16, VGG19, MobileNet, MobileNetV2, DenseNet169, and Xception). The proposed approach is divided into two main phases. In the first phase, we apply transfer learning and a fine-tuning process, which allows the networks to adjust to the specific features. During the second phase, two ensemble learning techniques are explored: voting and bagging, each helping to increase generalization and reduce prediction variance. In bagging, we apply the feature fusion of fine-tuned models, which enables us to achieve an accuracy of 99.44% using the decision tree classifier. These results surpass recent and existing works in this field, demonstrating the effectiveness of ensemble learning in leveraging model complementarity to enhance robustness and accuracy in identifying palm diseases.

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Corresponding Author:

Mohammed El Amin Kourtiche
Department of Mathematics and Computer Science, Faculty of Exact Sciences, Tahri Mohamed University
Independence Road BP 417, Bechar 08000, Algeria
Email: kourtiche.amin@univ-bechar.dz

1. INTRODUCTION

Date palm trees can generally be grown in arid and semi-arid environments and are extensively cultivated on the Arabian Peninsula, North Africa, and West Asia. Palm trees play a significant role in the agricultural economy of most of these countries. However, several diseases continuously threaten the quantity and quality of date fruit. Early classification of plant diseases allows farmers to implement the most effective prevention measures. Plant disease is a phenomenon that occurs due to abnormalities in the form, physiology, or behavior of plants. According to Vishnoi *et al.* [1], there are two types of plant diseases: abiotic diseases result from non-infectious agents in plants, such as physiological factors like sunburn and mineral deficiencies, while biotic diseases are caused by infectious agents, including bacteria, viruses, or fungi. Plant disease symptoms are evident in various parts of the plants. Nevertheless, plant foliage is the initial site of disease identification, and the symptoms of most diseases may first appear on the leaves [2]. Early and accurate diagnosis is one of the most crucial initial steps in mitigating losses from plant diseases.

Plant disease identification is an important challenge in the agriculture sector. In the past, agricultural experts and botanists primarily depended on their personal experience to identify disease

symptoms, often requiring manual inspection of plants and leaves. This approach was time-consuming and susceptible to bias and human error. By adopting modern agricultural techniques and disease management strategies, farmers can enhance the resilience of their date palm crops. This proactive approach ensures a stable yield and supports the livelihoods of communities dependent on this vital resource. Leveraging advanced technologies like image processing, computer vision techniques, and deep learning (DL) can significantly improve the identification of diseases, thereby supporting agricultural sustainability. The integration of these technologies not only aids in early disease detection but also enhances overall crop management practices, contributing to improved yields and reduced losses. Applications of artificial intelligence in agriculture are divided into different types of activities [3]: crop and soil monitoring, crop yield prediction, intelligent spraying, predictive insights, agriculture robot, and disease diagnosis.

Research background: using DL models, especially convolutional neural networks (CNNs), can lead to substantial improvements in the accuracy of plant disease detection, addressing the challenges posed by traditional methods. Alshehhi *et al.* [4] utilized three different CNN models: SqueezeNet, GoogleNet, and AlexNet to detect the discoloration in date palm leaves, which is essential for maintaining the health of these plants. The highest accuracy is 98%, achieved using the SqueezeNet model. Kursun *et al.* [5] explored the machine learning (ML) techniques. They utilized CNN models for feature extraction, such as Inceptionv3, SqueezeNet, and VGG16, as well as various ML algorithms for classification: K-nearest neighbors (KNN), support vector machine (SVM), random forest (RF), artificial neural network (ANN), and logistic regression (LR). ANN showed the highest accuracy at 83.8% with Inceptionv3. The study in [6] used the GoogLeNet model (M4) for classifying diseases impacting oil palm leaves based on their distinctive textures and also compared different optimizers, noting that the RMSprop optimizer yielded the highest accuracy of 93.22%. Alaa *et al*. [7] employed image processing techniques combined with ML to detect palm diseases. They focus on capturing both normal and thermal images of palm trees, which are then analyzed to identify signs of disease. The study employs CNN for distinguishing between leaf spots and blight spots, and SVM for detecting the red palm weevil. This dual approach aims to enhance the accuracy of disease detection. The accuracy for the classifier CNN achieved 97.9%, and for SVM, it reached 92.8%.

The study in [8] explored different CNN architectures, specifically InceptionV3, DenseNet, and MobileNet, to extract and analyze leaf characteristics for classification. MobileNetV2 emerged as the top-performing model, achieving an overall accuracy of 96.99%. Magsi *et al*. [9] extracted color, size, morphological, and texture features from the images using the hue, saturation, and value (HSV) color space and scale-invariant feature transform (SIFT), and applied the gray level cooccurrence matrix (GLCM) for texture analysis. Thereafter, the CNN is used to identify and classify the disease stages. The proposed mechanism achieved an accuracy of 89.4%.

The study in [10] focused on detecting white scale disease (WSD) in date palms using ML techniques, employing GLCM and HSV as feature extraction for WSD stage-wise classification. The framework classifies WSD into three infestation degrees using ML models, including SVM and KNN. The best accuracy of 98.29% is achieved by SVM with combined GLCM and HSV features. The study in [11] presented a hybrid model that identifies diseases in palm leaves. They combined the efficient channel attention network (ECA-Net) with transfer learning models ResNet50 and DenseNet201. The ECA-Net is designed to recover details across different scales, which is essential for capturing the nuances in leaf images. They utilized SVM for classification tasks. The model achieved 98.67% validation accuracy. The research conducted by [12] utilized DL models, VGG16, VGG19, ResNet50, and MobileNetV2, to classify date fruit type, ripeness, and identify three stages of WSD infestation in date palm leaflets. They also employed explainable AI (XAI) techniques to enhance the interpretability of the models. The highest accuracy, 99.7%, is achieved by using VGG16. Savas [13] investigated DL for palm disease detection in smart agriculture. Transfer learning and fine-tuning techniques are applied using pretrained models, and ensemble learning enhances generalization, with the Dirichlet ensemble technique achieving a 99% ROC AUC score.

The study in [14] introduced an innovative hybrid transformer DL framework called Swin-YOLO-SAM. This framework integrates four modules to achieve accurate detection, segmentation, and quantification of disease severity in date palm leaves. They used swin transformer for disease classification, YOLOv12 for real-time detection. In addition, they employed grounding DINO with SAM2.1 for precise segmentation of disease regions and vision transformer (ViT) with a regression head for severity prediction.

The classification accuracy achieved 98.91%. Based in [15], an ensemble system was proposed that combined both the HybridConv Mixer and ViT models to generate improved features for classification. This technique leverages the beneficial features of both models to achieve higher performance in date palm disease classification. The HybridConv Mixer component is designed to detect local disease features, while ViT is used to analyze image patches and capture long-range dependencies. This capability is essential for enhancing global feature analysis. The ensemble model achieved an outstanding performance, reaching 99.89% accuracy. In the literature, many studies in DL have also shown promising results, emphasizing the power of these methods to revolutionize plant disease diagnosis and management [2], [16]-[18].

Research purposes: plant disease identification has evolved rapidly in recent years; however, maintaining a balance between computational efficiency and practical applicability remains a significant challenge. Initially, numerous advanced methodologies are formulated and assessed using curated datasets like plant village [19]. These datasets frequently originate from controlled environments, mirroring laboratory settings, characterized by restricted fluctuations in illumination, background, and image acquisition parameters. Consequently, these models may exhibit difficulties in achieving robust generalization within intricate, real-world agricultural contexts, where the simultaneous presence of multiple diseases and diverse imaging conditions is commonplace. ViT have gained increasing prominence in recent literature due to their strong performance. Nevertheless, their practical deployment on edge devices is constrained by high computational complexity and inference latency. Therefore, there is a growing need for a reliable and lightweight system capable of efficiently detecting multi-class plant diseases in real-world scenarios while maintaining high accuracy.

The main objective of this work is the early identification and classification of date palm diseases, including three nutrient deficiencies and five other diseases. Our work is based on the dataset of [20], which is constructed from field data and encompasses numerous disease classes, unlike other studies that use datasets with only two or three disease categories. The main contributions of this research are as follows:

- We employed several transfer learning architectures. Subsequently, we selected the most promising models that provided the most accurate results. Six pre-trained models were chosen: VGG16, VGG19, MobileNet, MobileNetV2, DenseNet169, and Xception. In the initial step, we fine-tune the selected models to improve their accuracy.
- Two ensemble learning techniques are evaluated: the first is voting, which includes both hard and weighted soft voting, and the second is bagging using feature fusion strategy based on feature concatenation. Both techniques were evaluated on different scenarios.
- The data was gathered in real-world agricultural environments, and eight distinct diseases were classified with high accuracy.

The remainder of this paper is organized as follows: the second section describes our proposed method, the dataset preprocessing techniques, fine-tuning, and the ensemble learning techniques. The third section presents the experimental results and compares the performance of the proposed model with other models. The last section presents the paper's conclusion and future work.

2. METHOD

This section describes the datasets used and the methodological framework of the study. To overcome the limitations of an individual classifier, we utilize transfer learning by employing a set of pretrained CNN architectures: VGG16, VGG19, MobileNet, MobileNetV2, DenseNet169, and Xception. This study proposes two stages for performance optimization:

a. In the first stage, we apply transfer learning and fine-tuning to the six pre-trained models to enhance the models' generalization capability; more details on this will be given in the following subsections.
b. In this second stage, we evaluated two techniques of deep ensemble learning: the first is voting, which includes hard voting and weighted soft voting for different combinations of fine-tuned models, while the second ensemble learning technique is bagging. During this phase, we extracted the features from the training images of the fine-tuned models, and in order to generate the feature vectors, we performed a fusion strategy via direct concatenation of the feature vectors. We then passed these vectors as input to the bagging ensemble learning to train the classifier; our approach is illustrated in Figure 1.

2.1. Dataset

The dataset comprises images representing eight major disease categories affecting date palm leaves. It also includes healthy palm leaves as baseline. It contains 3089 processed images. Images were captured over three months (autumn and spring) from 10 real date farms in the Madinah region of Saudi Arabia [20]. Images were taken using smartphones and an SLR camera, focusing on infected leaves and leaflets. Figure 2 shows sample images from the dataset, including three physiological disorders (Figure 2(a), potassium deficiency; Figure 2(b), manganese deficiency; and Figure 2(c), magnesium deficiency), four fungal diseases (Figure 2(d), black scorch; Figure 2(e), leaf spots; Figure 2(f), Fusarium wilt; and Figure 2(g), rachis blight), one pest infestation (Figure 2(h), *Parlatoria blanchardi*), and one healthy condition (Figure 2(i)).

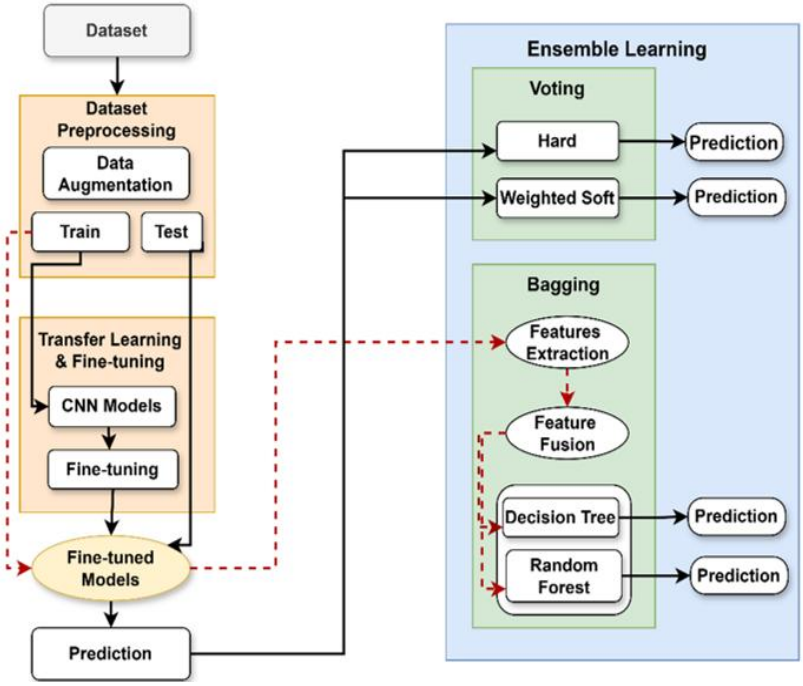


Figure 1. Block diagram of the proposed method

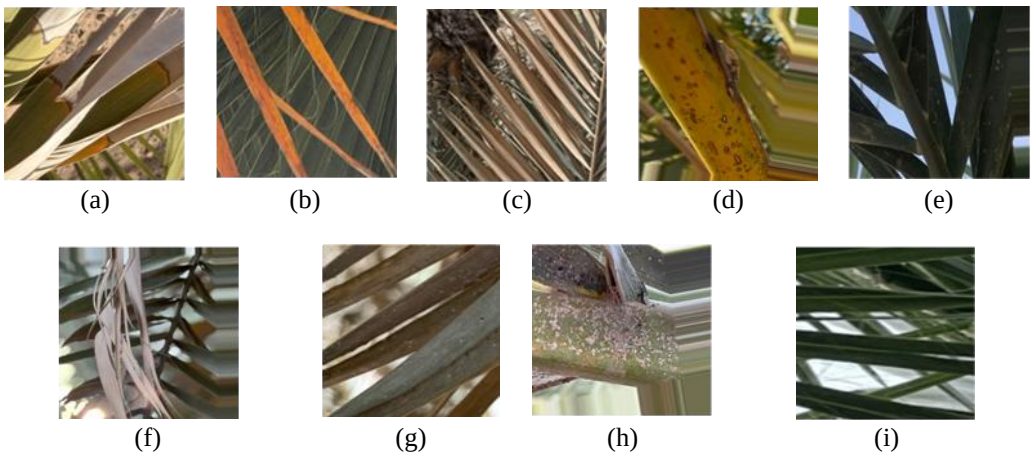


Figure 2. Sample images from the dataset; (a) K deficient, (b) Mn deficient, (c) Mg deficient, (d) black scorch, (e) leaf spots, (f) wilt fusarium, (g) rachis blight, (h) *Parlatoria blanchardi*, and (i) healthy

2.1.1. Data augmentation

The first thing to note regarding the dataset is its imbalance. To fix that, we applied a data augmentation technique that allows the generation of additional images from the original ones. Data augmentation involves applying various transformations such as translation, rotation, scaling, cropping, flipping, kernel filters, noise injection, and color space transformations. By implementing different data transformations, we can ensure that the models can generalize to new data and do not overfit the training set [21]. In our work, we used the following techniques: random rotation between -20° and +20°, horizontal shift up to 20% of the width, vertical shift up to 20% of the height, shear_range=0.2 (shearing transformation), random zoom in/out within a 20% range, and randomly flipping the image horizontally.

2.1.2. Data preprocessing

After data augmentation, we proceed to the preprocessing dataset. The images in the dataset were preprocessed from 300×300×3-pixel size to 224×224×3 and 229×229×3 according to the input of each model architecture. We randomly selected about 400 images for each class. The 3587 images in the dataset were

randomly divided into training (80%) and test (20%). The number of images for each class is shown in Table 1.

Table 1. Data augmentation and a balanced dataset

	K-	Mn-	Mg-	Black scorch	Leaf spots	Wilt fusarium	Rachis blight	*Parlatoria blanchardi*	Healthy
Dataset [20]	831	415	566	106	69	210	402	101	389
Our balanced dataset	400	400	400	400	400	400	400	398	389

2.2. Transfer learning in deep learning

Transfer learning is a technique in DL where a model developed for a task with large datasets is reused as the starting point for a model on a different but related task. It is particularly effective in domains like plant disease classification, where labeled data is limited or expensive to obtain. The primary benefit of transfer learning is that, rather than initiating the learning process from the beginning, the model leverages patterns learned from solving a similar problem [22]. The following provides a brief description of the CNN models in use.

VGG16 and VGG19 are deep CNNs characterized by a uniform architecture using 3×3 convolution filters, with VGG16 [23] comprising 13 convolutional layers and VGG19 extending to 16, both followed by fully connected layers, offering strong baseline performance for image classification tasks despite their high parameter counts.

MobileNetV1 [24] and V2 [25] are lightweight CNNs optimized for mobile and embedded applications, where V1 introduces depthwise separable convolutions to reduce computation, and V2 enhances this efficiency with inverted residual blocks and linear bottlenecks for improved accuracy and feature representation on low-resource devices.

DenseNet169 [26] is a deep CNN that leverages dense connectivity, where each layer receives input from all preceding layers. This promotes rich feature reuse and improved gradient flow. Xception the high-performance CNN architecture, which was inspired by the Inception network [27] uses depthwise separable convolutions in place of conventional convolutions and incorporates residual connections to effectively extract both spatial and channel-specific features.

2.3. Fine-tuning

To enhance model performance, we unfroze and fine-tuned the upper 10 layers of each model; a hyperparameter tuning procedure was applied to three key parameters. Specifically, the number of units in the dense layer was varied between 128 and 512 in increments of 128; the dropout rate was adjusted within the range of 0.2 to 0.4 to reduce the risk of overfitting; and two learning rates were tested: 0.001 and 0.0001, to control the rate of convergence during training. These hyperparameters were optimized using a random search strategy. For the multi-classification problem, the loss value was chosen as categorical_crossentropy.

Epoch numbers were chosen as 20, and the batch size values were determined as 16. According to the results, we notice a considerable improvement in accuracy after performing fine-tuning. Table 2 displays the results obtained after this step.

Table 2. Validation accuracy of the evaluated CNN models

Models	Xception (%)	MobileNet (%)	DenseNet169 (%)	MobileNetV2 (%)	VGG16 (%)	VGG19 (%)
Before fine-tuning	84.40	89.14	87.74	88.86	80.78	76.32
After fine-tuning	98.46	96.09	98.32	93.99	91.62	91.62

2.4. Ensemble learning

Ensemble learning is a combination of several different predictions from different models to make the final prediction. It aims to reduce the model error and maintain the model's generalization [28]. Bagging, boosting, stacking, and voting are the four major classes of ensemble learning algorithms.

2.4.1. Voting

Voting in the context of ML is a method to combine predictions from multiple models or classifiers to make a final decision or prediction. Instead of relying on an individual model, it employs the "wisdom of the crowd" concept to produce forecasts that are more accurate by using the aggregate judgment of multiple models [29]. There are two common types of voting techniques: hard and soft voting.

Hard voting: in hard voting, each model or classifier makes a prediction, and the final decision is based on the majority vote. Its formula is given in (1):

$$\hat{y} = \arg \max_{c \in C} \sum_{i=1}^{M} 1(y_i = c) \quad (1)$$

where: y_i class predicted by the model i.

M: total number of models.

C: set of all classes.

1(y_i=*c*): indicator function=1 if model *i* predicts class c, otherwise 0.

Soft voting: in soft voting, not only are the majority votes considered, but also confidence scores from each model's predictions are taken into account. The confidence scores for each class are summed up, and the class with the highest total confidence score is chosen. Its formula is given in (2):

$$\hat{y} = \arg \max_{c} \frac{1}{M} \sum_{i=1}^{M} p_{i,c} \quad (2)$$

where: $p_{(i,c)}$ is the probability predicted by the model *i* for class *c*.

Weighted soft voting: similar to soft voting, but some models are weighted more heavily than others. We use a weight for each model's probability, as shown in (3):

$$\hat{y} = \arg max_{c} \frac{\sum_{i=1}^{M} \omega_i \cdot p_{i,c}}{\sum_{i=1}^{M} \omega_i} \quad (3)$$

where: ω_i is the weight assigned to model *i*.

2.4.2. Bagging

Bagging, or bootstrap aggregating, is an ensemble learning technique that generates multiple subsets of the original training dataset through bootstrap sampling and independently trains a classifier on each subset. By introducing diversity among the training samples, bagging helps reduce model variance and mitigate overfitting. Each classifier produces an individual prediction, and the outputs are subsequently aggregated to obtain the final prediction, typically through majority voting for classification tasks or averaging for regression problems [29].

2.5. Performance analysis parameters

The metrics given in (4)-(7) were used to evaluate the performance rate of our ensemble model. Precision, recall, F1 score, and accuracy were determined by quantifying the predicted classes based on the following quantities: the number of false negatives (FN), false positives (FP), true negatives (TN), and true positives (TP). The mathematical representation's definition is outlined (4)-(7):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

$$\text{F1 score} = 2 \times \frac{\text{recall} \times \text{precision}}{\text{recall} + \text{precision}} \quad (7)$$

2.6. Experimental procedure

Experimental studies were conducted on a virtual machine in a cloud environment. The system used a Tesla P100 GPU with CUDA 12.6 and 16 GB of GPU memory. Python version: 3.10.12 and TensorFlow version: 2.17.1. to determine the best ensemble learning to enhance accuracy, various combinations (scenarios) of models are evaluated in the voting and bagging techniques. We apply in (1) for hard voting and (3) for weighted soft voting, and the weights attributed are the accuracy of the models. For the bagging technique using the RF classifier, we use 5-fold cross-validation to validate the model. The hyperparameters were optimized using a random search strategy. In the case of the DT classifier, for each combination of hyperparameters, we attempt to optimize the model with the following parameters: n_estimators=90, max_samples=0.8, bootstrap=true. Table 3 displays the validation accuracy results.

Table 3. Ensemble learning results

CNN Models						Voting		Bagging	
VGG16	VGG19	MobileNet	Mobile NetV2	Densenet169	Xception	Hard (%)	Weighted soft (%)	DT classifier (%)	RF classifier (%)
		✓		✓		97.49	98.74	98.46	98.04
	✓	✓		✓		98.18	98.32	98.32	98.60
			✓	✓		96.37	98.18	98.46	98.32
			✓	✓	✓	98.46	98.60	**99.44**	99.16
		✓			✓	97.21	98.74	98.32	98.46
		✓		✓	✓	**98.60**	**99.16**	99.30	99.16
✓			✓		✓	97.34	98.18	98.32	98.88
				✓	✓	**98.60**	99.02	99.02	**99.30**

3. RESULTS AND DISCUSSION

After applying the ensemble learning, we notice that in the case of voting, the weighted soft voting technique outperforms hard voting in all cases. By using the DenseNet169 and Xception models, we achieve an accuracy of 99.02%, which represents a gain of 0.56% in comparison to the best one in the individual case. Furthermore, to get a higher level of performance, we incorporate MobileNet, which enabled us to achieve an accuracy of 99.16, which is a gain of 0.7% in comparison to the best one in the individual instance. In the second part of the evaluation, utilizing the bagging technique, which produces better results in most cases regarding the voting technique, we observe that the aggregation of the three models, DenseNet169, MobileNet, and Xception, enables us to get an accuracy of 99.30%, reflecting an improvement of 0.84%. MobileNetV2, despite its lower individual performance (93.99%), improved the bagging performance compared to the MobileNet model, obtaining the highest accuracy of 99.44%, with an improvement of 0.98%. Figure 3 shows the confusion matrix of this best model combination, and its classification report is in Figure 4.

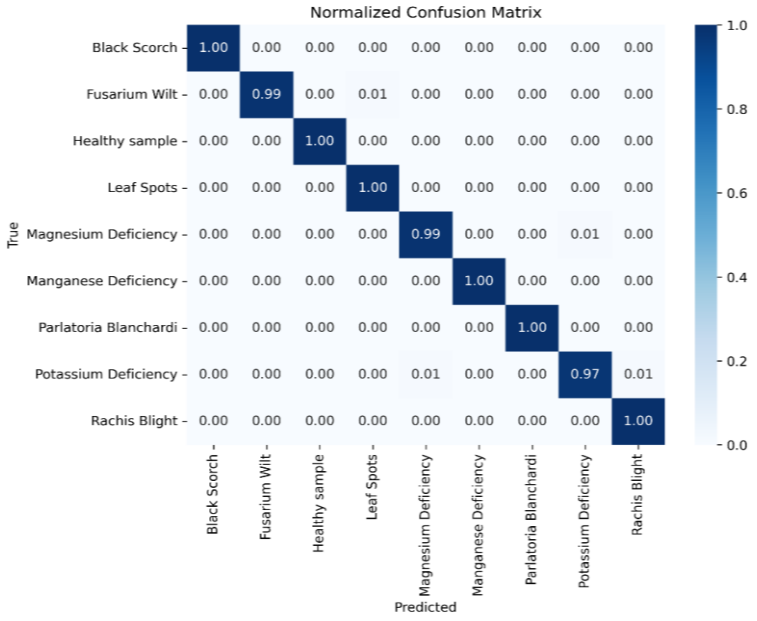


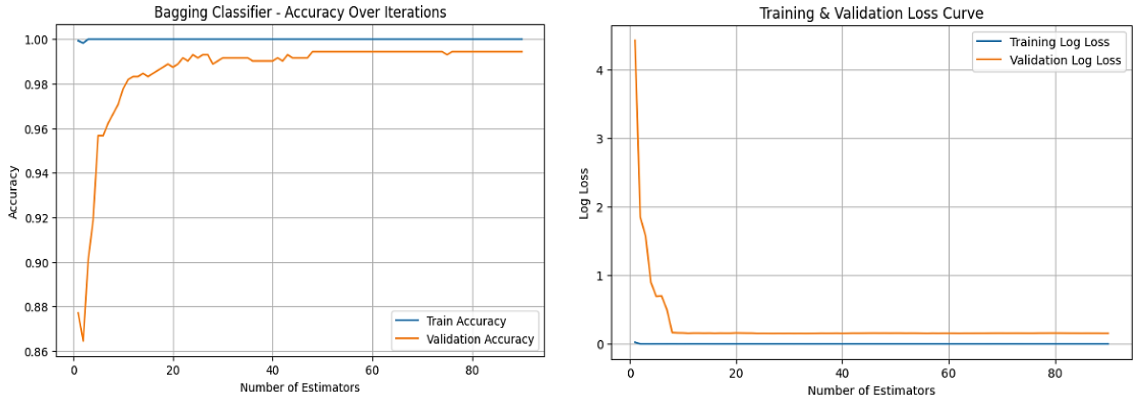
Figure 3. Confusion matrix of bagging with the DT classifier model

When looking at the normalized confusion matrix in Figure 3, it demonstrates that the majority of disease categories (black scorch, leaf spots, manganese deficiency, *Parlatoria blanchardi*, and rachis blight) and the healthy sample were classified with excellent performance, attaining 100%. However, there is the fusarium wilt disease, which was occasionally misclassified as leaf spots (1%); and nutrient deficiencies like magnesium deficiency, which showed slight confusion with potassium deficiency (1%), and the highest confusion was observed for potassium deficiency, achieving the classification of 97% and small misclassifications toward magnesium deficiency and rachis blight. These errors are likely due to the visual similarity of symptoms, especially among nutrient-deficiency classes, where overlapping discoloration and texture characteristics may reduce separability.

	precision	recall	f1-score	support
Black Scorch	1.00	1.00	1.00	80
Fusarium Wilt	1.00	0.99	0.99	80
Healthy sample	1.00	1.00	1.00	77
Leaf Spots	0.99	1.00	0.99	80
Magnesium Deficiency	0.99	0.99	0.99	80
Manganese Deficiency	1.00	1.00	1.00	80
Parlatoria Blanchardi	1.00	1.00	1.00	79
Potassium Deficiency	0.99	0.97	0.98	80
Rachis Blight	0.99	1.00	0.99	80
accuracy			0.99	716
macro avg	0.99	0.99	0.99	716
weighted avg	0.99	0.99	0.99	716

Figure 4. Classification report of bagging with the DT classifier model

The advantage that allowed MobileNetV2 to surpass MobileNet is its feature representations, including the new concepts like inverted residuals and linear bottlenecks, which led to increasing diversity and reducing correlated errors with Xception and DenseNet169. Figure 5 shows the accuracy and loss curves of the model. Figures 5(a) and (b) show the accuracy and loss curve of the model. We notice that the accuracy increases with the number of estimators and reaches the highest value at 50, and remains constant after.



(a) (b)

Figure 5. Plots of; (a) accuracy and (b) log loss of the best model

Our proposed model gets a score of 99.44%, much higher than the competing models and more than the results obtained from the approach of [8], [14] for the same dataset. The different models from previous studies on identifying palm leaf diseases are provided in Table 4.

Table 4. Comparison results with previous studies

Ref.	Model/approach	Dataset	Performance results (acc) (%)
[7]	CNN and SVM	Kaggle dataset and thermal images dataset	97.9
[4]	SqueezeNet, GoogleNet, and AlexNet	Date palm leaves	98
[10]	SVM, KNN, RF, and LightGMM	Date palm WSD	98.29
[11]	ResNet50, DenseNet201, ECA-Net, and SVM	Infected date palm leaves by Dubas insects	98.67
[8]	InceptionV3, DenseNet121, and MobileNetV2	infected date palm leaves for palm tree disease detection and classification	96.99
[13]	MobilenetV2, ResNet50, ResNetRS50, Dirichlet ensemble technique	Infected date palm leaves by Dubas insects, Kaggle date palm dataset	99
Our model	Xception, DenseNet169, MobileNetV2, and bagging (decision tree classifier)	infected date palm leaves for palm tree disease detection and classification	**99.44**

The advantages of our model are numerous: the model uses the advantages of different CNN models by applying ensemble learning; our model takes less computation time. Consequently, it is more precise and effective. Our model is a good candidate to be used in real-world smart agricultural systems because to its outstanding performance, especially the MobileNetV2 augmented bagging configuration with an accuracy of 99.44%. The inverted residuals and linear bottlenecks in the architecture of MobileNetV2, which provide architectural diversity, not only improve classification accuracy but also reduce computational overhead in scenarios where resource constraints are an important issue. This is a key benefit for edge deployment.

4. CONCLUSION

This study demonstrates that ensemble learning substantially enhances the accuracy of classifying palm leaf diseases compared to individual CNNs. While Xception and DenseNet169 emerged as the strongest individual models, incorporating MobileNet or MobileNetV2 in ensemble frameworks provided diversity that improved robustness. Among all evaluated approaches, the bagging ensemble composed of Xception, DenseNet169, and MobileNetV2 achieved the best overall performance, with an accuracy of 99.44%. These results confirm that model diversity is an important factor in ensemble learning, in addition to the individual strength of each classifier. Although the proposed ensemble model achieved excellent performance, this study has some limitations; the experiments were conducted using an existing dataset, which may not fully capture the variability of real agricultural environments. In particular, environmental factors such as lighting variation, shadows, and background complexity were not explicitly evaluated and may affect the performance of the model in practical deployment scenarios. Furthermore, the observed confusion between visually similar nutrient deficiency classes (magnesium vs. potassium) and certain disease pairs (fusarium wilt vs. leaf spots) indicates that visual symptoms alone may prove insufficient for resolving diagnostically challenging cases. The model has also not been benchmarked on edge computing platforms or validated through real-time field trials.

Future directions offer multiple possibilities to enhance and consolidate this research. We intend to perform on device benchmarking on smartphones and other edge platforms, real time field trials in operational plantation environments, and integration with internet of things (IoT) sensor networks for multimodal disease diagnosis that fuses visual classification with environmental parameters. Robustness evaluations will be conducted under varying lighting conditions, background complexity, and practical agricultural acquisition settings. Furthermore, future studies will expand the dataset by adding emerging diseases and inter-regional data to improve generalizability.

The model's computational efficiency positions it as a strong candidate for deployment across the smart agriculture technology stack—mobile applications for smallholder farmers, IoT gateways for continuous plantation monitoring, and drone-based systems for large-scale aerial surveillance—enabling scalable, data-driven disease management that enhances food security, reduces pesticide dependency, and improves farmer livelihoods through sustainable precision agriculture practices.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Mohammed El Amin Kourtiche	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
Ikram Kourtiche		✓	✓			✓		✓		✓	✓			
Ahmed Bouida	✓			✓	✓					✓	✓		✓	

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

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in [Infected Date Palm Leaves Dataset] at https://data.mendeley.com/datasets/g684ghfxvg/2, doi: 10.17632/g684ghfxvg.2.

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BIOGRAPHIES OF AUTHORS



Dr. Mohammed El Amin Kourtiche is currently an associate professor at the Department of Computer Science, Faculty of Exact Sciences, University Tahri Mohamed, Bechar, Algeria. He obtained a degree in Computer Science at Tahri Mohamed University, Bechar, Algeria, in 2007. He then received a magister's in NTIC at the University of Science and Technology at Mohamed Boudiaf, Oran, in 2014, and a Ph.D. from the University of Tahri Mohamed, Bechar, Algeria in 2021. Member of the Information Processing and Telecommunications Laboratory (LTIT). His research areas are image processing, machine learning, and deep learning. He can be contacted at email: kourtiche.amin@univ-bechar.dz.



Ikram Kourtiche is a Ph.D. student in Computer Science at Tahri Mohamed University, Bechar, Algeria. She obtained a master's diploma in Computer Science, specializing in computer systems and networks at Tahri Mohamed University, Bechar, Algeria, in 2021. Member of the Information Processing and Telecommunications Laboratory (LTIT). Her research interests focus on the field of smart farming using artificial intelligence, such as machine learning and deep learning. She can be contacted at email: kourtiche.ikram@univ-bechar.dz.



Dr. Ahmed Bouida is currently an associate professor at the Department of Material Sciences, Faculty of Exact Sciences, University Tahri Mohamed, Bechar, Algeria. He received a magisters in Electronics at the University of Djillali Liabes, Sidi Bel Abbes, Algeria in 1998. and a Ph.D. from the University of Tahri Mohamed, Bechar, Algeria, in 2021. Member of the Information Processing and Telecommunications Laboratory (LTIT). His research interests are oriented in image processing, biometric and medical images, electronic engineering, and computer engineering. He can be contacted at email: bouida.ahmed@univ-bechar.dz.