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Ensemble learning weighted average meta-classifier for palm diseases identification

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ABSTRACT

Crop diseases lead to significant losses for farmers and threaten the global food supply. The date palm, valued for its nutritional benefits and drought resistance in desert climates, is a vital export crop for many countries in the Middle East and North Africa, second only to hydrocarbons. However, various diseases pose a threat to this important plant. Therefore, early disease prediction using deep learning (DL) is essential to prevent the deterioration of date palm crops. The aim of this paper is to apply a robust ensemble method (EL) combining tree transfer learning (TL) models Resnet50, DenseNet201, and InceptionV3, and compares its performance with the CNN-SVM model and the tree TL models mentioned previously. The models were applied to a date palm dataset containing three classes: White scale, brown spot, and healthy leaf. The training and validation sets were applied to a public dataset, while the testing set was applied to a local dataset captured manually to check the model's performance. As a result, we considered that the ensemble method gave very satisfactory results compared to other methods. Our hybrid model reached a testing accuracy of 98% while achieving an amazing training and validation accuracy of 99.94% and 98.14%, respectively.

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1. INTRODUCTION

Plants are a primary source of food for the global population [1]. Agriculture is regarded as a crucial sector with significant effects on life and economic in several nations. Due to the substantial population growth, meeting people's dietary needs and improving the quality and quantity of crops has gained significant importance. The transition to smart agriculture has become inevitable to achieve food security goals [2], while the use of traditional methods and improper management leads to the loss of agricultural products [3]. According to a report by the food and agriculture organization (FAO), it is estimated that the population of the whole world will approximately rise up to 9 billion in a few years. However, the production within the agricultural sector needs to be improved to at least 70% in order to satisfy the food demands of human beings [4].

Sweet and palatable, eaten as a main course, the date palm or Phoenix dactylifera L, is one of the earliest plants known to humans in pre-Saharan and Saharan regions. It belongs to the Arecaceae family and has been cultivated since ancient times [5]. Date cultivation has had a significant impact on this region's history. In this harsh desert climate, dates are essential for the survival of a sizable human population. They hold special significance as a symbol of fecundity and fertility, linked to societal values, traditions, and rituals [6] that have been inherited by numerous generations [7]. Extensively, dates are used in the food processing industry for making juice, jam, jelly, and syrup, or being consumed alone as such in their fresh or dried forms. Besides, local citizens may rely on this fruit, that is rich in nutrients like carbohydrates, proteins, vitamins, lipids and minerals that are essential for human health [5]. Every component is utilized, including the trunk and leaves, which are employed in ancient building methods and basketry [8]. Date palm in many nations in the Middle East and North Africa, has a big impact on the environment, society, and economy. This crop is the most important one in Algerian Sahara agriculture, affecting jobs, sedentarization of people, and products. It is projected to consist of around 800 species and over 17 million palm trees [9]. ranks fourth globally in date production, yielding 1,131,605 metric tons annually across 169,380 hectares. Dates are also Algeria’s most valuable agricultural product export, with 15,000 tonnes exported annually [9], [10].

The date palm is severely limited by environmental factors such as saline soil, long-term droughts, high temperatures, desertification [8]. However, these same conditions also encourage the existence of microorganisms which contributes to the occurrence of pests and diseases. In general, a variety of diseases, including Bayoud, leaf smut, red palm weevil, mealy bugs, and mites, can afflict date palm trees [10], [11]. It has a devastating effect on palm trees; in just one century, a disease like Bayoud (Fusarium oxysporium f. albedinis) has killed three million trees in southwestern Algeria [12]. The nature and symptoms of these diseases vary in their form, often appearing on the leaves [7]. Conventional approaches for identifying plant diseases, which involve observing the disease with the unaided eye or using skilled laboratory procedures, take time and necessitate ongoing plant observation [13]. Farmers often grapple with the challenge of not seizing the opportunity to prevent these illnesses. While using modern approaches would help to avoid diseases in general and in case of palm trees in particular and take necessary measures in time saving costs and laborer’s, there is still a need to work on a practical and efficient method of addressing these issues. Easy to use and convenient via a mobile app would make it helpful to date palm farmers [14]. Several machine learning (ML) and DL techniques, used by researchers to categorize and recognize palm images, including date palm diseases and date fruit, are presented in this section.

Noutfia and Ropelewska [5] aims to categorize five date palm fruit varieties using ML algorithms by extracting texture features from fruit images. The models, including combined textures selected from all 12 colors channels, achieved an average accuracy of 98%. In the study from Al-Shalout *et al.* [7], convolution neural network (CNN) and support vector machine (SVM) algorithms are suggested to detect date palm diseases. The results show that CNN is more effective, achieving an accuracy of 99.87% when the size of the dataset increases. Employing image augmentation technology. The study was applied to four common diseases dataset: bacterial blight, brown spots, leaf smut, and white scales [11]. Built a framework that uses ML techniques (SVM, KNN) and EL methods (light gradient boosting machine, random forest (RF)) to classify the stages of infestation by white scale disease in date palm trees based on their leaflet images. The framework extracts texture features from images. The best performance accuracy of 98.29% achieved by SVM [12]. Applied a supervised ML techniques (KNN, SVM, Naive Bayes, and AdaBoost) to recognize the gender of date palms at the seedling stage using an image of infected date palm leaves by dubas insects, the SVM algorithm yielded the most accurate results with 97% accuracy [13]. Developed a framework for date recognition based on color, shape, and size features, they employed CNN to three types of dates: Aseel, Kupro, and Karbalain, acquired 97.2% accuracy. Ahmed and Ahmed [15] used TL of inception and ResNet on a 2,631 total varied sizes images, achieving accuracy of 99.62% and 100%, respectively, to classify three classes of palm disease. Magsi *et al.* [16] implemented a CNN to recognize palm disease at different stages, in 1,200 date palm leaves disease images have been collected manually, achieved an accuracy of 89.4%. The experimental results discussed in the paper [17] are based on five stages using a dataset of 27 date classes with 3,228 images. The first stage applied ML algorithms. The second stage, a DenseNet TL was applied, and in the stage tree and four, fine-tuned was applied to achieve the best model’s classification. In the fifth stage, regularization was implemented, achieving a validation accuracy of 97.21%, and a test accuracy of 95.21%. Abu-zanona *et al.* [18] suggested CNN model applied in a dataset contain tree palm leaves diseases achieves an accuracy of 99.10%, the performance of the proposed model is evaluated and compared against VGG-16 and MobileNet. Khriji *et al.* [19] three different ML techniques, SVM, artificial neural networks (ANN), and K-Nearest neighbor (KNN) have been employed for classification based on color, shape and size features. applied to six date fruit varieties in Oman, The highest accuracy of 99.20% achieved by the ANN classifier. In [20] this work two classifiers were utilized to classify three diseases. VGG to differentiate between leaf spots and blight spots, and SVM for red palm weevil pest. The results for VGG and SVM showed a success rate of accuracy 97.9% and 92.8% respectively. The researchers presented in [21] a hybrid model that combines the efficient channel attention network (ECA-Net) with DenseNet201 and ResNet50 though TL, achieving remarkable accuracy rates of 99.54% for training and 98.67% for validation.

The goal of this study is to leverage artificial intelligence (AI), particularly ML and DL, to enhance agriculture by using images of infected palm leaves to identify two common diseases (white scale and brown spots), with a third class containing healthy leaves. Unlike previous work, which largely focused on ML or TL models individually with public datasets, this study addresses a gap by introducing EL combining pretrained CNNs on a local dataset. Several challenges were encountered during this study, including a shortage of specialists in palm tree disease in the Bechar region of Algeria, which made it difficult to diagnosis and collect images for a local palm tree dataset. Moreover, the scarcity of information on palm diseases compared to other plant diseases is likely due to their occurrence in specific geographical areas. The main contributions of this paper include the application of a hybrid method combining CNN- SVM, TL on ResNet50, DenseNet201, and inceptionV3. additionally, our proposal of EL on the same TL models. The performance of the proposed EL, based on a weighted average meta-classifier, was compared with the TL and CNN-SVM results using a local test dataset from the Bechar region.

The paper's remaining section is arranged as follows: section 2 deals with the dataset, the proposed model and the methodology that has been used to solve the problem. Section 3 deals with experiments performed to on the given problem and results obtained for the same, and a comparison between different models. Finally, The conclusion and the future scope in section 4.

2. METHOD

Our workflow, shown in Figure 1, represents a robust ensemble method with a weighted average meta-classifier, combining three TL models, ResNet50, DenseNet201, and InceptionV3 to identify leaf palm diseases, and its performance was compared with CNN-SVM and individual TL models using a local test dataset from the Bechar region in Algeria.

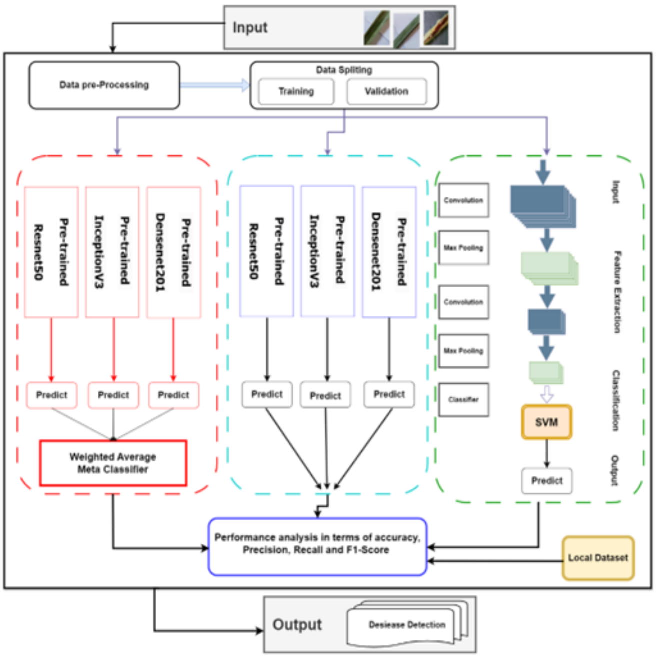


Figure 1. Proposed workflow diagram

2.1. Dataset description

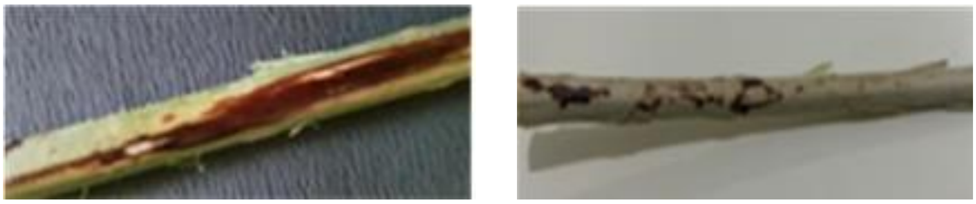
The presented model is trained and assessed using a public date palm dataset from Kaggle [1], The dataset is containing a total of 2,631 labelled date palm leaflets for 3 classes (healthy, brown spots, and white scale). For the purpose of image-based identification which includes, training and evaluation phase where the performance of classification algorithms is evaluated, it is necessary to have huge datasets to receive better results. To enhance the dataset and increase the credibility of the performance evaluation, additional images were captured locally and combined with the public dataset. Resulting in a total of 430 samples for testing the models. The public dataset, which has been divided into training and validation images for the suggested models. The distribution of the date palm leaf disease images is presented in Table 1.

Table 1. Distribution of dataset categories

Categories	Number of samples
Brown spots	470
White scale	958
Healthy	1203
Total	2631

The validation set contains 20% of the total palm leaf photos, whereas the training set has 80% of the entire leaf dataset images [21]. Each set includes an uninfected class and two infected classes of date palm leaf diseases. Figure 2 presents a selection of sample images from the datasets used in this study, showcasing healthy and diseased leaves from both public and local datasets. Specifically, Figure 2(a) displays a healthy leaf sample, and Figure 2(b) shows a sample image of white scale disease from the public dataset. Figure 2(c) illustrates a sample of brown spot disease from the public dataset, while Figure 2(d) depicts another example of brown spot disease captured from our local dataset.

(a) (b)



(c) (d)

Figure 2. Samples for each palm class in order: (a) healthy leaf, (b) white scale leaf disease, (c) brown spots leaf disease from the Kaggle dataset, and (d) brown spots disease captured locally

2.2. CNN-SVM model

The CNN-SVM model is a hybrid approach that combines the strengths of CNN with SVM to improve classification accuracy. SVM is a supervised learning algorithm that attempts to find a best separating hyperplane that is embedded into the given feature spaces. By maximizing the margin between the dissimilar classes, SVM aims to reduce the number of misclassifications [22]. The hybrid CNN-SVM model applies the SVM model in place of the conventional SoftMax activation function found in the last layer of a CNN. This kind of adjustments gives a chance for the CNN to automatically extract features from the input data, which are finally classified by the SVM [23]. During training in this study, various pre-processing techniques are used to enhance model performance. For instance, rescale parameter set to 1/255 normalize pixel values into [0, 1] to speed up convergence. Input images are resized to 224×224 pixels. A batch size of 32 ensures a balance between computational efficiency and performance. The model uses a squared hinge loss function for multi-class classification on an SVM output layer.

2.3. Transfer learning (TL)

TL is a ML technique that employs knowledge from a prior model to tackle a new related problem. Applying such TL method, demonstrate one's knowledge from a big-labelled dataset like ImageNet to a plant disease classification task. Info transferring is a part of narrowing down the generalization error and shortening the network training time by utilizing the model which is already developed as a new tool. This outcome is attributable to the fact that TL helps us train DL models firstly when done more quickly and accurately because knowledge and patterns in a particular domain are transferred to the other one [24], [25]. The multitude of CNN models already pre-trained are a huge number available for use. Top three pre-trained

CNNs models: InceptionV3, ResNet50, DenseNet201 has been selected due to their unique advantages and complementary capabilities in feature extraction and image classification.

Each model was trained for ten epochs with consistent parameters, including a dense layer with 512 units, ReLU activation, an input shape of 224×224×3, and a dropout rate of 0.3 to avoid overfitting. To preserve learned features, the initial ten layers of each model were frozen. After the training and validation stage, these TL models was tested on our local dataset. The models are defined in the following section.

2.3.1. InceptionV3

Proposed by Szegedy *et al.*, is a deep CNN architecture that demonstrated its performance and won the first place in the 2014 Large-scale ImageNet visual recognition challenge (ILSVRC). Inception-v3 takes in input Shape of 244 by 244 pixels, Unique elements of this model include the fully connected (FC) layer, batch normalization, and convolutional layers, which means it is different than its predecessors [26].

2.3.2. Resnet50

He *et al.* (2016) invented the short form residual network (ResNet), a DL architecture frequently used for image classification applications. Their architecture uses skip connections, allowing the gradient to skip some layers in between and flow directly from the input to the output, which consists of 50 layers, to address the issues of vanishing gradients and network degradation in DL. Information is propagated through the network using residual blocks, which improves prediction accuracy [27].

2.3.3. Densenet201

Densenet201 Is a sophisticated DL architecture designed to tackles the vanishing gradient problem and is a part of the DenseNet family. With 201 layers, it surpasses the original structure in complexity. Densenet201 is composed of stiff dense blocks with tightly packed layers. Every layer focuses on taking in information from the layers before it, mapping the resulting features. This method promotes feature reuse and makes smooth gradient propagation easier, which eventually improves the performance of the model [24].

2.4. Ensemble learning (EL)

With the help of fusion methods, different models are merged in ensembles modelling in order to reach the higher-level prediction confidence and better generalization in ML domain. Notwithstanding, since single model errors next to other models can be corrected, the team's score becomes much better than that of any given model alone. The three primary types of EL techniques are boosting, stacking, and bagging [25], [28]. In this study three TL models: ResNet50, InceptionV3, and DenseNet201, were combined to developed an EL model. The final predictions were made using a weighted average meta-classifier. Predictions were collected from each of the trained base models and stored in an .h5 file. The base models were trained on a publicly available palm dataset. Accuracy, F1-score, precision, recall, and other performance metrics were used to assess each base model's effectiveness using a local testing dataset captured in Bachar region. Each model was given a weight according to how well it performed; models with larger weights performed better. The final predictions and performance of the weighted average EL were obtained using the local dataset.

3. RESULTS AND DISCUSSION

3.1. Experimental setup

To perform the necessary experiments, the study was implemented through Python scripts and executed on Google Colaboratory (Google Colab), leveraging its access to graphics processing units (GPUs) and Tensor Processing Units (TPUs) capabilities up to 12 GB of RAM. The date palm dataset was uploaded to Google Drive and imported into the Colab environment using a laptop equipped with an Intel i5 processor and running Windows 10. The algorithms were developed using several libraries, such as Scikit-learn, Seaborn, NumPy, Pandas, and Matplotlib. Google Colab was selected for its efficiency and ease of use, offering a reliable and speedy platform for DL models training and analysis.

3.2. Evaluation metrics

Accuracy, recall, precision, F1-score, and confusion matrix are the performance evaluation metrics used for analyzing the ML models. For a given class, accuracy is defined as the rate of correctly identified samples out of the total number of samples in that class. This metric is defined with the (1).

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

tp: true positives, *tn*: true negatives, *fp*: false positives, *fn*: false negatives.

Precision, recall, and F1-score are estimated utilizing the mathematical (2)–(4) respectively.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - score = \frac{2(\text{precision}*\text{recall})}{\text{precision}+\text{recall}} \quad (4)$$

High precision indicates that every predicted image is a palm leaf class, regardless of the number of misclassified palm diseases. On the other hand, good recall or (sensitivity) represent the measure of the proportion of the actual positive palm leaf class that were classified correctly, regardless of how many things were incorrectly classified. The F1-score is the harmonic measure of precision and recall. Ultimately, the performance of the various ML models under investigation was interpreted using confusion matrices.

3.3. Results analysis and discussion

This study utilized various of ML models to categorize date palm leaf images. Furthermore, the benefit of the suggested approach is that palm plant illnesses can be recognized at an early stage. For this purpose, EL, CNN-SVM and three TL models, run on palm dataset containing 2,631 images divided on 3 classes tested in our local dataset containing 430 images. Moreover, there is a lack of studies focusing on applying EL to local palm datasets, which are essential for enhancing accuracy in real-world scenarios with EL. By combining several TL models to improve palm disease categorization, this work closes the gap. The following discussion provides a comprehensive evaluation of these models' performance.

Training a CNN using a SVM classifier demonstrated significant efficiency in palm disease classification. This approach yielded a commendable training accuracy of 95.83% and a validation accuracy of 94.17 %. However, when tested on the local dataset, The CNN-SVM achieved the lower testing accuracy of 94%, which was the lowest among all models evaluated. TL employing pre-trained models such as InceptionV3, DenseNet201, and ResNet50, was also assessed. Very acceptable results were yielded by the InceptionV3 model: the training and validation accuracy were 99.86%, 97.35%, respectively. The testing accuracy comprised 97%. The DesneNet201 and Res-Net50 architectures showed not bad outcomes too: 99.82% and 99.01%, 96.61% and 97.44%, 96% and 97% for training, validation and testing accuracy, respectively. The EL technique was the most impressive in this session, utilizing a weighted average meta-classifier, combined predictions from the previously mentioned TL methods. By assigning weights based on each model's performance, EL achieved the highest performance among all models. the performance analysis, in terms of training and validation accuracy, precision, recall and F1 score of all models, is illustrated in Table 2. EL achieved a training accuracy of 99.94% and a validation accuracy of 98.14% after ten epochs, as shown in Figure 3, with a testing accuracy of 98%, indicating its robustness in classifying local samples, all EL prediction results on the test dataset have been illustrated in Figures 4. Specifically, Figure 4(a) represents the classification test report, while Figure 4(b) shows the EL confusion matrix with disease labels.

Table 2. Model's performance in terms of evaluation metrics

Models	Evaluation metrics	Brown spots	Healthy	White scale	Training accuracy	Validation accuracy
CNN-SVM	Precision	0.98	0.92	0.92		
	Recall	0.97	0.93	0.93	0.9583	0.9417
	F1-Score	0.97	0.92	0.92		
TL InceptionV3	Precision	1.00	0.95	0.95		
	Recall	0.96	1.00	1.00	0.9986	0.9735
	F1-Score	0.98	0.97	0.97		
TL DenseNet201	Precision	0.97	0.96	0.96		
	Recall	0.96	0.97	0.97	0.9982	0.9661
	F1-Score	0.97	0.97	0.97		
TL ResNet50	Precision	1.00	0.95	0.95		
	Recall	0.95	0.99	0.99	0.9901	0.9744
	F1-Score	0.97	0.97	0.97		
Ensemble learning	Precision	0.97	0.99	0.99		
	Recall	1.00	0.96	0.96	0.9994	0.9814
	F1-Score	0.99	0.98	0.98		

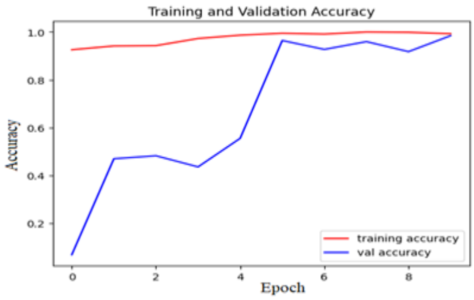
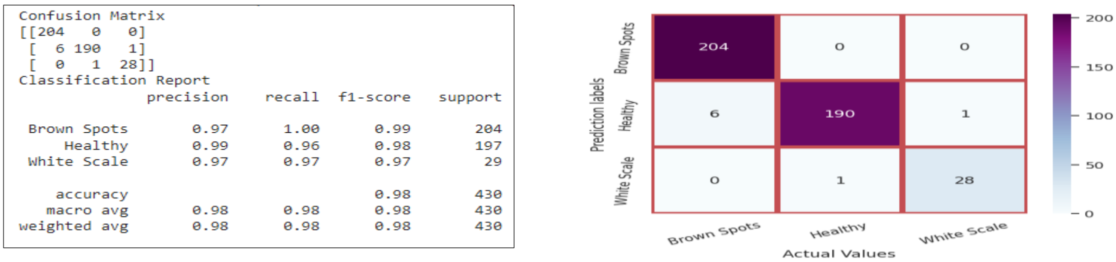


Figure 3. Training and validation accuracy using ensemble method



```
Confusion Matrix
[[204   0   0]
 [  6 190   1]
 [  0   1  28]]
Classification Report
              precision    recall  f1-score   support

 Brown Spots       0.97      1.00      0.99       204
     Healthy       0.99      0.96      0.98       197
 White Scale       0.97      0.97      0.97        29

    accuracy                           0.98       430
   macro avg       0.98      0.98      0.98       430
weighted avg       0.98      0.98      0.98       430
```


(a) (b)

Figure 4. EL model performance on test dataset (a) EL classification report and (b) EL confusion matrix

Compared to prior studies as shown in Table 3, our approach not only demonstrates superior accuracy but also addresses the challenges of working with a locally collected dataset, unlike studies [15], [18], and [20], which primarily rely on public dataset. Moreover, only a few studies, such as [11], have employed EL, but they too were restricted to public datasets. The weighted average meta-classifier and the base pretrained models used in our EL distinguishes our work from others, offering a novel method for leveraging the strengths of multiple chosen models to achieve better results. And provides a more robust solution, enhancing overall performance and reducing the risk of misclassification. This finding supports our hypothesis that EL would outperform individual models, particularly when applied to local datasets, as demonstrated in studies [7] and [16]. Additionally, the results indicate that integrating diverse models for feature extraction can significantly improve classification outcomes.

Table 3. Accuracy comparison of our proposed study with similar literature studies

Ref /Year	Approach	Palm leaf dataset classes	Dataset source	Best accuracy
[7]/ 2020	CNN, SVM	Brown spots, White scale, Bacterial blight, Leaf smut, Healthy	Kaggle, Jordan valley	99%.
[11]/ 2020	SVM, KNN, and EL: RF, LightGBM.	Healthy, White scale	Kaggle	98.29%
[15]/ 2023	Resnet and TL: Inception	Brown spots, Healthy, White scale	Kaggle	99.62%
[16]/ 2020	CNN	Sudden decline syndrome	Collected manually	89.40%
[18]/ 2022	CNN, VGG-16 and MobileNet.	Brown spots, White scale, Bacterial blight, Leaf smut, Healthy	Kaggle	99.10%
[20]/ 2020	VGG, SVM	Blight Spots, Leaf Spots, Red palm weevil	Kaggle	97.90%
[21]/ 2024	TL: ResNet50, DenseNet201	Dubas, Bug, Healthy, Honey	Kaggle	98.67%- 99.54%
Our model	EL: TL (ResNet50, InceptionV3, Densnet201)	Brown spots, Healthy, White scale	Kaggle, Local- captured dataset	98.14%- 99.94%

The implications of this research extend beyond the specific case of palm disease classification. The success of the EL model suggests that similar EL could be applied to other agricultural challenges, potentially transforming disease management practices. Future research may explore the development of mobile applications and web-based platforms that leverage these models for real-time detection, making these advanced techniques easy to use by farmers. Additionally, expanding the research to include a wider variety of plant diseases and environmental conditions could further enhance the model's utility and robustness.

Given that palm trees take many years to bear fruit, neglecting to implement effective disease detection methods, such as those proposed in this study, could lead to significant agricultural losses, particularly in desert regions where palm cultivation is economically vital. The integration of advanced ML models, especially through EL, offers a promising approach to improving the accuracy and efficiency of disease detection in agriculture, providing substantial benefits for both farmers and the broader agricultural industry. Adopting these methods is crucial for ensuring sustainable agricultural practices.

4. CONCLUSION

This study explored three ML techniques to classify palm leaf disease dataset: CNN-SVM, TL using (DenseNet201, InceptionV3 and ResNet50), and EL. The outcomes illustrate the potential of these models to assist farmers in predicting and managing palm diseases, thereby contributing to more effective and sustainable agricultural practices. CNN-SVM achieved a decent testing accuracy of 94%, in comparison, TL models showed higher testing accuracies, with DenseNet201, InceptionV3 and ResNet50 reaching 96%, 97%, and 97%, respectively. Notably, our EL model, employing a Weighted Average meta-classifier, achieved the highest testing accuracy of 98%. Showcasing its ability to enhance accuracy by combining multiple high-performing classifiers. This result aligns with and extends previous research, highlighting the benefits of ensemble techniques in agricultural applications. Importantly, our study's El model, applied to a locally captured palm dataset, represents a significant advancement in palm disease classification, especially given the challenges of limited local data and complex diseases identification. Future research should focus on refining these models and developing practical tools, such as a mobile apps, for real-time palm disease identification. Additionally, extending this approach to other plant diseases and environment could further improve its applicability.

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