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LSTM-BASED DISCRIMINATION OF DATE FRUIT (*PHOENIX DACTYLIFERA* L.) BASED ON SELECTED CONVOLUTIONAL NEURAL NETWORK FEATURES

– Research paper –

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Abstract: Date palm (*Phoenix dactylifera* L.) is one of the most valuable domesticated fruit trees characterized with thousands of varieties that grow in different arid regions. Because of high diversification, discrimination between date varieties at different post-harvest handling and production stages is necessary. In this study, five different CNN (Convolutional Neural Network) models, namely ResNet18, ResNet50, MobileNet, GoogleNet and DenseNet, are used as fine-tuning tools for the classification of five Moroccan date fruit varieties: 'Mejhoul', 'Boufeggous', 'Assiane', 'Aziza' and 'Bousthammi'. The features of MobileNet, the most successful of these CNN models, were analyzed with an RNN (Recurrent Neural Network)-based LSTM (Long short-term memory) architecture. In addition, feature selection is performed for MobileNet features to achieve a more successful classification with fewer features. As a result of LSTM-based classification of both original MobileNet features and selected features, higher classification accuracy was achieved in comparison with other CNN models. Moreover, LSTM with selected features provided the most successful discrimination ability. The accuracies obtained as a result of the classification of original MobileNet features and selected features with LSTM were 99.63% and 99.70% respectively. Overall, the results indicated that the LSTM-based architecture with fewer features improves the success of existing CNN models for date fruits.

Keywords: Mejhoul, date cultivar, Classification, Convolutional Neural Network, Feature Selection, Long short-term memory.

INTRODUCTION

Date *(Phoenix dactylifera* L.) is one of the most important agricultural product in North African and Middle Eastern countries contributing to the nutrition of human beings since ancient times (up to 6000 BC). In addition to its historical importance, date fruit has been accepted as a staple food in the Arabian Gulf region, as it has a religious and cultural background (Manickavasagan et al., 2021). The total date fruit production in 2022, especially in Egypt, Iran, Morocco, Algeria and Saudi Arabia, was about 9.74 million tons (FAOSTAT 2024). Although, there are more than 5000 date varieties worldwide, with less than 10% of them were identified and commercialized (Kamal-Eldin and Ghnimi 2018, Khalid et al. 2017).

Date fruit varieties with many different sizes, tastes, weights and colours are grown worldwide, and 'Mejhoul', 'Boufeggous' (Noutfia et al. 2019), 'Deglet Nour', 'Ajwa', 'Sukkary' (Rahmani et al. 2014) are highely appreciated by consumers seen their quality and nutritional attributes. Thus, date fruit is rich with carbohydrates, calcium, fibres, minerals as zinc, iron and potassium (Idowu et al. 2020, Muhammad 2014, Nasiri et al. 2019). This fruit specie is a very good antioxidant and can be used for anti-inflammatory purposes and improving vascular health (Al-Dashti et al. 2021). In addition to the fleshy part of the date fruit, the kernel had an important role in the date fruit processing industry, thanks to the mannan fibres that provide great potential for developing fibres-rich healthy food products (Ghnimi et al. 2017).

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The colour, taste and texture of the date fruit differ also according to several factors such as maturity stage, pre- and postharvest treatments, as well as variety. Because of the resemblance between date fruit varieties, different discrimination techniques based on molecular, spectroscopic, and chromatographic identification and biochemical attributes, as well as genotyping by sequencing methods (Thareja et al. 2018) were developed to distinguish between different date fruit varieties. These techniques are consuming time, destructive, tedious and expensive. Thus, there is a need to adopt non-destructive (Noutfia and Ropelewska 2023a, Noutfia and Ropelewska 2023b), fast and easy discrimination methods and techniques, especially for date fruits. The automatic and smart determination of date palm varieties would be very useful at industrial scale, especially in Arab countries where date fruit consumption and commercialization are high (Alturki et al. 2020). Techniques called "computer vision for automatic fruit discrimination" were recently applied for many agricultural products, such as cherries (Ropelewska et al. 2021), wheat (Sabanci et al. 2020), tomatoes (Ropelewska et al. 2022a), plums (Ropelewska et al. 2022b), and cranberries (Zielinska et al. 2017), showing promising results in terms of classification/ discrimination accuracy.

In this context, the objective of this study was bring insight about an improved neural network approach to classify five varieties of date fruit based on a dataset of 450 date fruit images using Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN). The innovative approach for the varietal classification of date fruit was related to the application of both fine-tuned CNN models (ResNet18, ResNet50, MobileNet, GoogleNet and DenseNet) and RNN-based LSTM-based architecture.

MATERIALS AND METHODS

Generating date fruit image data

Five date fruit varieties 'Mejhoul', 'Assiane', 'Aziza', 'Boufeggous' and 'Bousthammi' were obtained from a cold unit in the south-east of Morocco and were used in the experiments. From each variety, 90 mature fruits were used. Before imaging, fruit samples were washed and cleaned to obtain images. Date fruit images were acquired using a digital camera and a light source. Fruits were imaged on a white background for a strong decomposition of each object and the TIFF format was selected during the saving process. The sample images of five types of date fruit are presented in Figure 1.

Classification using CNN models for date fruits distinguishing

The methodological steps used for date fruit classification are shown in Figure 2 and detailed in the subsections of this "methodology section". After the creation of date fruit dataset, each date fruit in the captured images was analysed individually. For this, image processing-based techniques are used. After the creation of individual and suitable date fruit images for classification, data augmentation was applied to enhance the performance effect for deep networks. After the augmented images were separated for training and testing, the first classification was performed with CNN models. Then the feature selection and RNN steps were applied to the best CNN model.

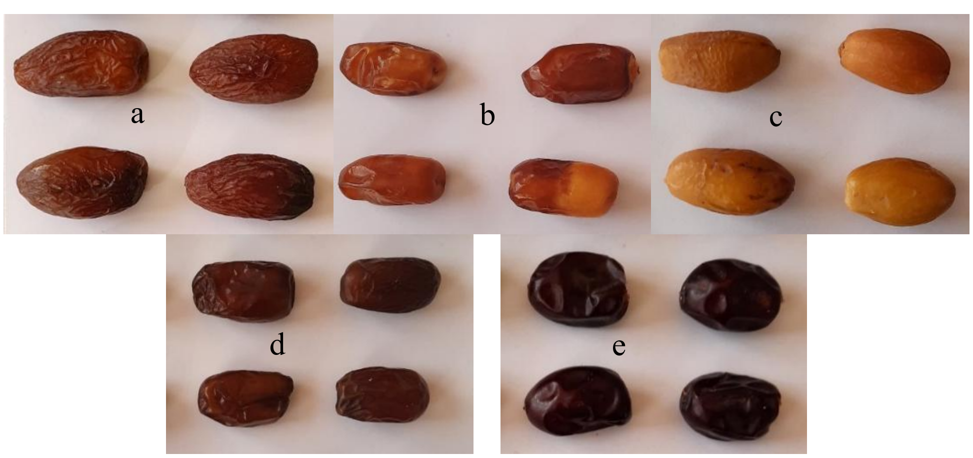

Figure 1. Date fruit varieties (a) 'Mejhoul', (b) 'Assiane', (c) 'Aziza', (d) 'Boufeggous', (e) 'Bousthammi'

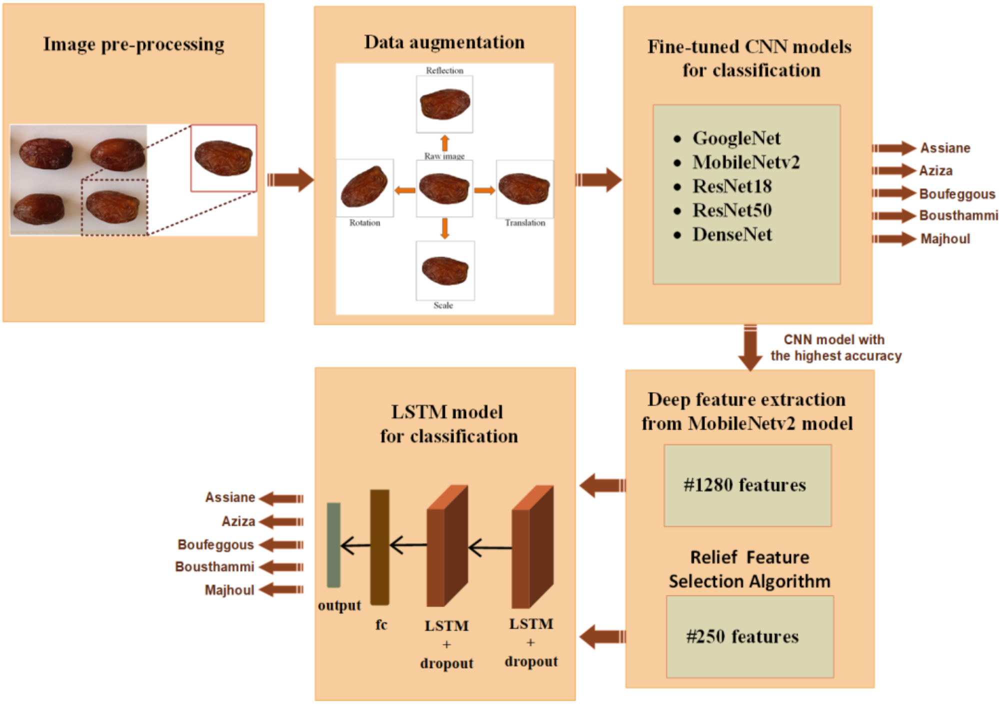

Figure 2. Classification steps using CNN models for date fruits distinguishing

Pre-Processing

During the image acquisition, it was ensured that the date fruits grouped on a white background didn't touch each other. During group-imaging of date fruit, the raw images had a resolution of 1977×2765 pixels. These raw images were converted first to binary images using the Otsu method (Otsu 1979), and the noise in the images was removed. In addition, the borders of each date fruit in the binary image were determined. Individual date fruit images were created from the denoised image using the borders of date fruits in the binary image. Each date fruit was cropped at 300x300 pixels. The background of the cropped date fruit has been removed to eliminate its effect on classification and it was exactly the same. A sample individual date fruit image created as a result of image preprocessing is shown in Figure 3.

Data Augmentation

In deep architecture, the data must contain enough samples for the model to be successfully trained. For this reason, datasets with many data are more preferred for more successful discrimination. Therefore, to ensure data diversity, this study applied data augmentation methods such as reflection, rotation, scaling and translation to raw images as seen in Table 1.

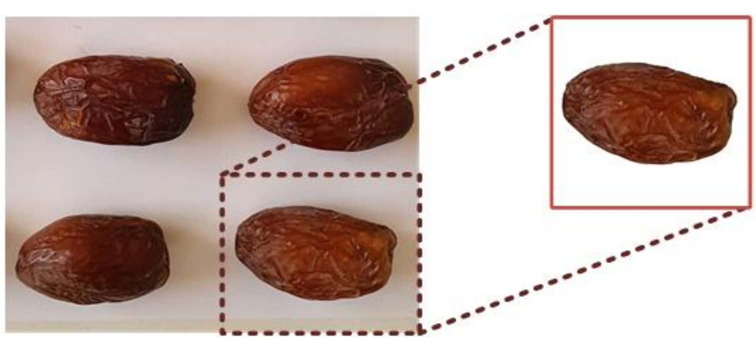

Figure 3. The preprocessing step of date fruit images

Table 1. Lower and upper limits of data augmentation methods

Techniques	Lower Limit	Upper Limit
Reflection	-	-
Rotation (Degree)	-45°	45°
Scale (Percentage)	80%	120%
Translation (pixel)	-20 px	+20 px

Considering the techniques and limit ranges shown in Table 1, a sample of data augmentation output of a cropped date fruit image is shown in Figure 4. In this way, many different images of the same date fruit sample are obtained. In the dataset used, each variety contained 90 images. As a result of the data augmentation, the amount of data for each variety was increased to 900.

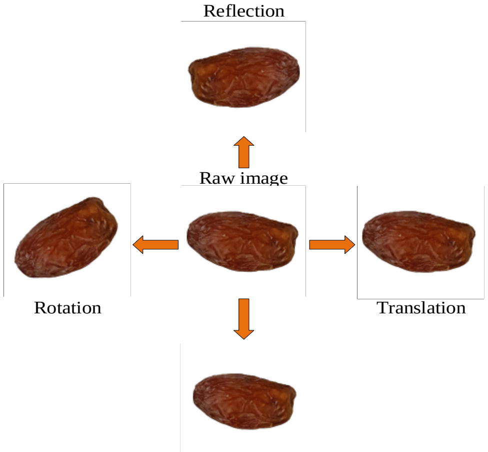

Figure 4. The results of data augmentation techniques on a date fruit

Date Fruit Classification

After augmentation step, data was classified with deep models. First, classification is made with five different CNN models. Finally, feature selection and LSTM-based ultimate classification are performed according to the success of the CNN models. Detailed information is explained below.

CNN-Based Classification

After achieving data augmentation, images were classified with five different CNN models. CNN architectures consisted of cascading convolutional layers, pooling layers, and fully connect layers in different combinations. Convolution (in two dimensions) is performed on the image with convolution layers, allowing the obtention of 2D features of the image. The pooling layer down samples the matrix in the output of the convolution layer and the feature matrix size is reduced.

Fully Connected (FC) Layers are generally in the last layers of CNN models. Feature matrices after convolution and pooling are associated with target information via FC layers. As a result, network training is performed and different CNN models resulted from combining these layers differently (Aslan et al. 2022, O'Shea and Nash 2015).

In this study, CNN models used in date fruit classification are GoogLeNet (Szegedy et al. 2015), ResNet18 (He et al. 2016), ResNet50 (He et al. 2016), DenseNet (Huang et al. 2017) and MobileNetv2 (Howard et al. 2017, Sandler et al. 2018), that differ from each other in terms of architecture, layers, depth, parameters, etc. For the classification of date fruit samples belonging to the five varieties with the CNN models given above, minor modifications were made to the existing model architectures, namely fine-tuning CNN. For this, FC and classification layer in the last layers of CNN models were restructured for five classes (SoftMax). The input layer of all CNN models used requires a 224 × 224 image. Therefore, the augmented date fruit images were resized and were loaded as input to the CNN models (Figure 5). The training-test ratio was determined as 70%-30% and performance metrics for training and test results are discussed in the results section.

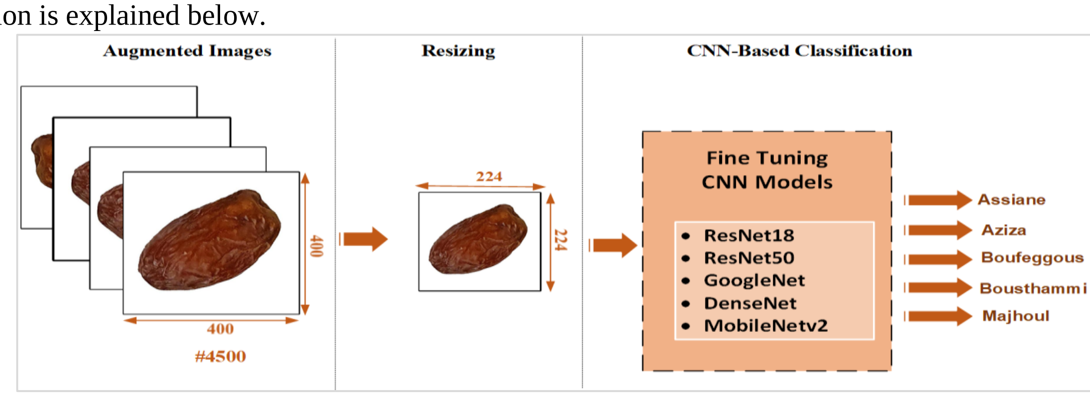

Figure 5. Classification of date fruit images with CNN models

Feature Selection and LSTM-Based Classification

Long Short-Term Memory (LSTM), a variant of RNN, (Hochreiter and Schmidhuber 1997) was used in this study. Although LSTM networks are designed to analyse temporal data, recent studies such as (Aslan et al. 2021, Cong et al. 2018, Sabanci et al. 2022) have proven that RNN-based architectures can also produce interesting results on independent data. The date fruit images used in this investigation are also independent and no temporal relationship between data was found. Therefore, this study takes advantage of the powerful feature extraction capability of RNN-based LSTM to distinguish date fruits as shown in Figure 6. The extracted features through LSTM layers are associated with target classes via FC and classification layers. The target classes of the network are date fruit varieties. The parameters set for the layers and training of this designed network are shown in Table 2. These values are determined by trial and error.

The network shown in Figure 6 showed the RNN-based architecture. The train-test ratio is determined as 70%-30%. The features given to the LSTM network are those extracted by CNN. The aim is to increase the success of existing CNN models with the LSTM architecture. In this context, the features of the most successful CNN models described in the previous section are given as input to the LSTM network. With these features, the LSTM is trained and tested for date fruit classification. However, the number of features in the LSTM entry is too large (1280 Features in Figure 6) at this step. To ensure more successful discrimination with fewer features, feature selection was performed. For this, the features extracted with CNN are reduced with the Relief feature selection algorithm (Kira and Rendell 1992, Urbanowicz et al. 2018). As a result, the number of CNN features is reduced to 250 (Figure 6). With these fewer features, training and testing for the date fruit are carried out again. Deep learning-based experimental studies of the proposed method are carried out using a computer with Intel Core i7-7700HG CPU, NVIDIA GeForce GTX 1050 4 GB, 16 GB RAM. In the application, firstly, the pre-processed, augmented and resized date fruit images are classified with the ResNet18, ResNet50, MobileNet, GoogleNet and DenseNet models. With these CNN models, 70% of the augmented 4500 date fruit data are trained and then the powerful trait of this trained model is evaluated with the test data. The confusion matrix, and the values of accuracy, sensitivity, specificity, precision, F1-score and MCC were determined as stated in Equations 1-6.

Table 2. LSTM Parameters.

LSTM-1			LSTM-2			FC	
Number of hidden units	State Activation Function	Gate Activation Function	Number of hidden units	State Activation Function	Gate Activation Function	Output Mode	State Activation Function
200	$tanh$	$sigmoid$	200	$tanh$	$sigmoid$	last	$tanh$
Training Parameters							
Optimizer			Max. Epoch	Mini Batch Size		Learning Rate	
Adam			50	512		0.001	

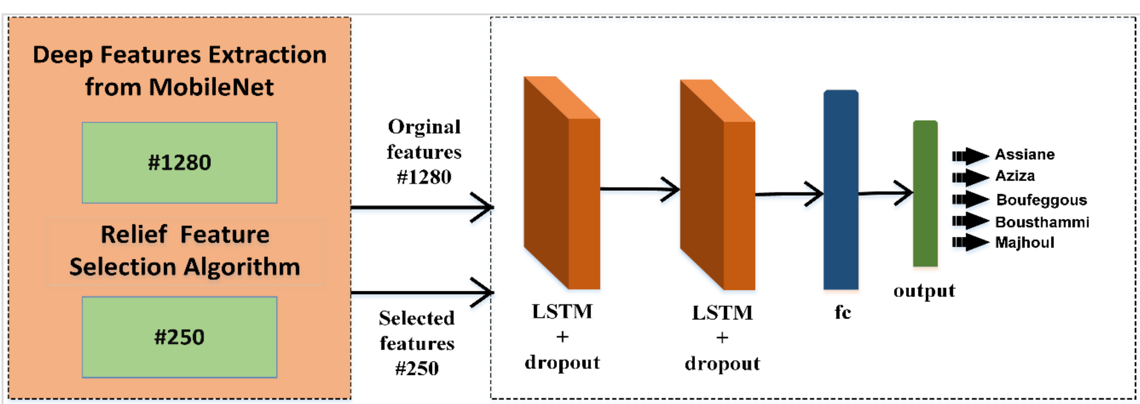

Figure 6. Classification of date fruit images with BiLSTM models

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} x100 \tag{1}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$F1 - score = \frac{2TP}{2TP + FP + FN} \tag{5}$$

$$MCC = \frac{(TP * TN) - (FN * FP)}{\sqrt{(TP + FN) * (TN + FP) * (TP + FP) * (TN + FN)}} \tag{6}$$

TP: True Positive TN: True Negative FP: False Positive FN: False Negative

RESULTS AND DISCUSSION

The discrimination ability of each CNN model on the test data is shown by the confusion matrices in Figure 7. Labels 1, 2, 3, 4 and 5 shown in the error matrices correspond to the 'Assiane', 'Aziza', 'Boufeggous', 'Bousthammi' and 'Mejhoul' varieties, respectively. When the confusion matrices are examined, it was clear that the CNN models provided a very successful performance in general. In particular, the 5-label Mejhoul is the most successfully classified type, distinguished with 100% accuracy by all other models except MobileNetV2. Similarly, the 4-label Bousthammi type is completely correctly classified by the MobileNet, GoogleNet, and DenseNet models. ResNet18, ResNet50 and GoogleNet distinguish the 2-label Aziza type with 100% accuracy. In general, CNN models performed more inaccurate classification for the Assiane and Boufeggous date fruit varieties. Considering the overall performance of the models on five date fruit varieties, the highest classification accuracy is achieved with MobileNet at 99.48%. The lowest classification accuracy was calculated with GoogleNet as 94.37%. The classification accuracy of all models is shown in Table 3.

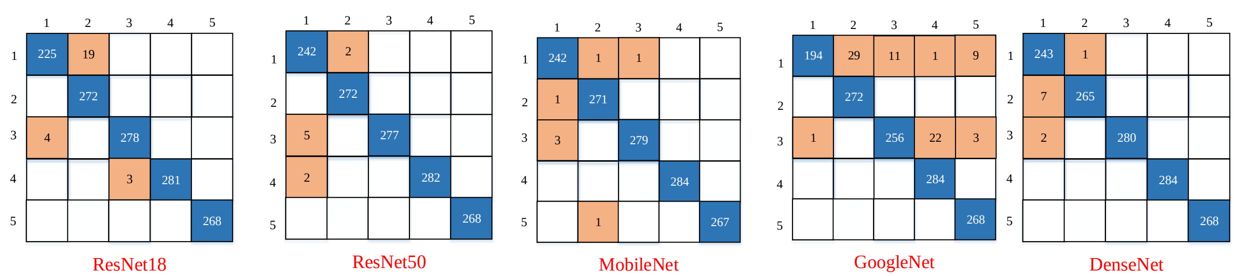

Figure 7. Confusion matrices of CNN models

Table 3. Performance metrics of CNN models

Model	Acc. (%)	Sens.	Spec.	Prec.	F1-Score	MCC
ResNet18	98.07	0.9795	0.9952	0.9813	0.9800	0.9755
ResNet50	99.33	0.9934	0.9984	0.9929	0.9931	0.9915
MobileNet	99.48	0.9948	0.9987	0.9946	0.9947	0.9934
GoogleNet	94.37	0.9406	0.9858	0.9479	0.9410	0.9295
DenseNet	99.26	0.9926	0.9982	0.9921	0.9923	0.9905

Table 3 also includes different performance metric values for each CNN model, such as specificity, F1-score, precision, sensitivity, and MCC. The formula for each of these metrics, including accuracy, is shown in Eq. (1)-Eq. (6). These values provide an unbiased evaluation of model performances. The sensitivity, specificity, precision, F1-score and MCC values of MobileNetV2 were respectively 0.9948, 0.9987, 0.9946, 0.9947 and 0.9934. These values confirmed that MobileNetv2 with the highest classification accuracy provided unbiased classification. In this context, the highest correctness among CNN models has been achieved with MobileNetV2. Figure 8 showed the accuracy (%), loss graph of training and testing (validation) steps of date fruit classification performed with MobileNetV2. This graph showed that MobileNetv2 provided successful training and validation without any overfitting.

As mentioned before, this study aimed to increase the success of existing CNN models with LSTM-based architectures. In this context, the features of the MobileNetV2 CNN model, which differentiates the date fruit most strongly, are fed into the designed LSTM architecture. MobileNetV2 included 1280 features in total. These features are extracted separately for training and test data. Therefore, the LSTM architecture shown in Figure 6 is initially designed with 1280 inputs. However, this number of features is large, while it is more desirable to achieve a similar classification success with fewer features. Therefore, this study selected 250 features from the original MobileNetV2 features with the Relief algorithm. Consequently, the LSTM architecture shown in Figure 6 is also designed with 250 inputs and training is carried out with the selected features.

The training and loss graphs of both the 1280 feature (original) LSTM and 250 feature (selected) LSTM architectures are shown in Figure 9. In addition, the confusion matrices of the test data obtained after both training and testing phases are presented in Figure 10. The performance metrics values obtained according to these confusion matrices are also given in Table 4.

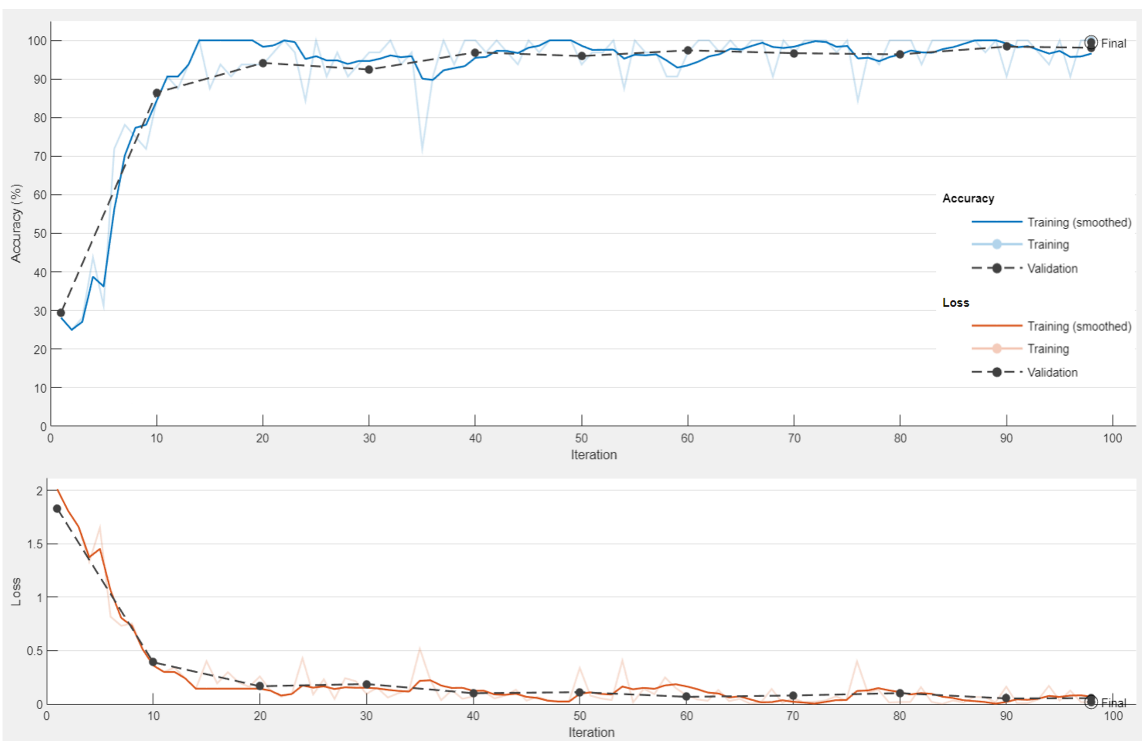

Figure 8. Training and loss graphics of MobileNetv2 model

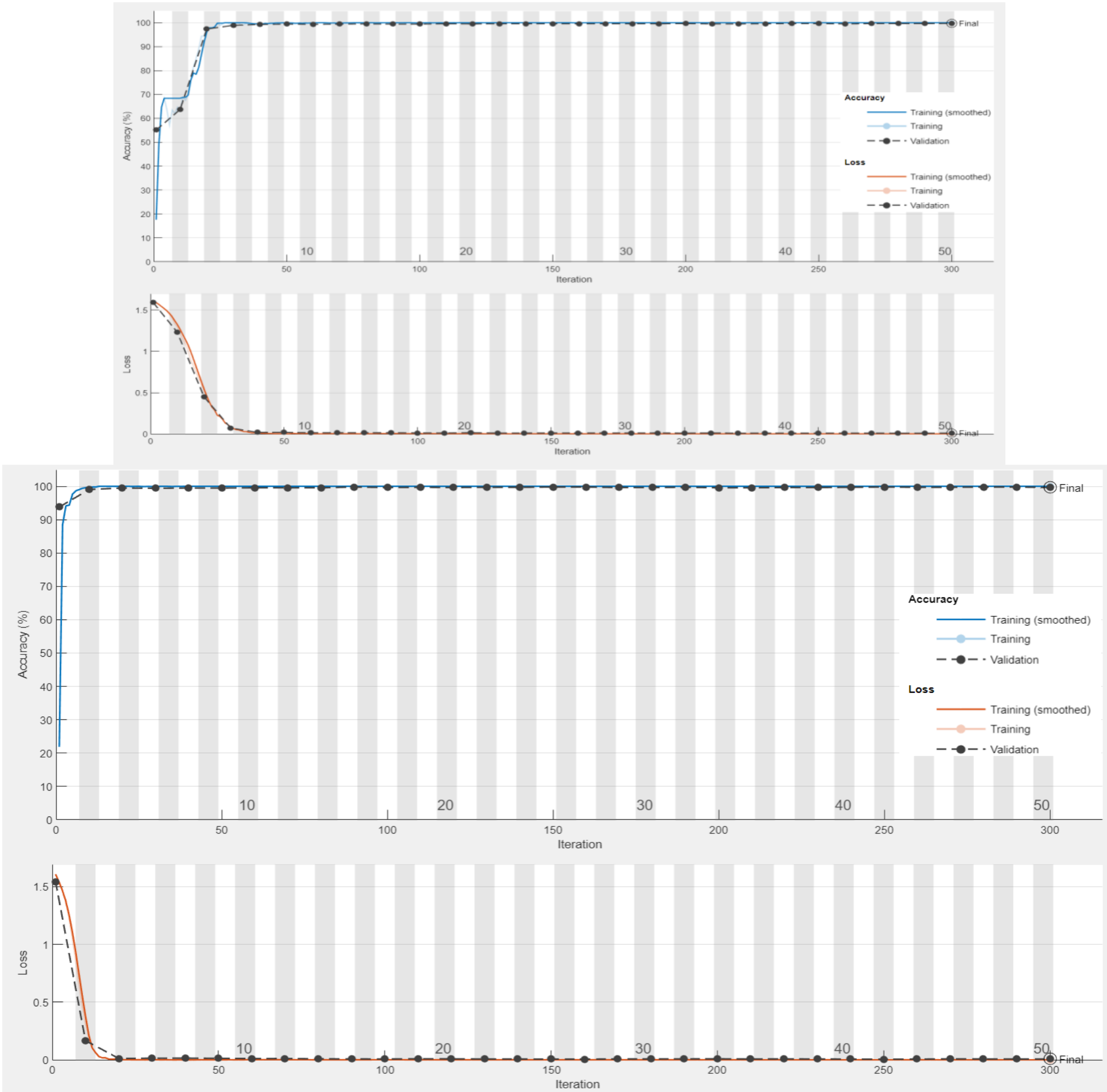

Figure 9. Training and loss graphs for LSTM-based architectures (a: 1280 features, b: 250 features)

All features

	1	2	3	4	5
1	243	1			
2	1	271			
3	1		280	1	
4				284	
5		1			267

Selected features

	1	2	3	4	5
1	243	1			
2		272			
3	1		280	1	
4				284	
5		1			267

Fig. 10. Confusion matrices obtained according to all (original) and selected features of MobileNetV2

Table 4. Performance metrics obtained as a result of the LSTM model using all features and selected features.

Model	Acc. (%)	Sens.	Spec.	Prec.	F1-Score	MCC
All Features (#1280)	99.63	0.9963	0.9991	0.9962	0.9962	0.9953
Selected Features (#250)	99.70	0.9970	0.9993	0.9970	0.9970	0.9963

According to the results of the LSTM architecture in Table 4, it was reported that more correct performances were obtained than MobileNetV2 in both LSTM structures. In the first stage, while the classification accuracy obtained with MobileNetV2 is 99.48%, LSTM models perform 99.63% and 99.70% more accurate classifications. Indeed, when the current CNN features are given as input to the LSTM architecture, date fruit varieties are distinguished more correctly. In addition, it was found that feature selection has a positive effect on classification success. This indicates that 250 selected features have stronger discrimination ability than 1280 features.

DISCUSSION

The previous artificial intelligence-based studies on the automatic classification of date fruit can be divided into two. Although early studies usually use traditional machine learning methods, later studies use deep learning methods. While various features such as color, shape and texture must be extracted for machine learning-based methods, these steps are performed automatically in deep learning. Morphological features of images are mostly used for machine learning-based discrimination of agricultural products (Koklu et al. 2021).

Some studies that classify the date fruit with machine learning algorithms are as follows: Koklu et al. (2021) created 898 images containing seven different types of date fruit. For machine learning methods, they extracted a total of 34 features, including morphological, shape and color, with image processing techniques from images. Then, the stacking method combining these two methods was applied. The classification accuracy by the stacking method was 92.8%. As a result of combining with stacking, a more successful classification was achieved than the other two machine learning algorithms. Abi Sen et al. (2020) extracted six different features based on color, shape and texture features for the classification of date fruits according to machine learning methods. They used SVM, ANN, DT and Random Forest algorithms to classify these features. The authors used the four-class dataset from the study by Hossain et al. (2018). At the end of the study, SVM provided the most successful classification with 73.8% accuracy. Muhammad (2015) presented a machine-learning-based study to classify 800 date fruit images in four classes based on color, shape, and texture. To extract features from the images, texture features were extracted from images in two different color spaces (RGB and YCbCr) with Local Binary Pattern (LBP) and Weber Local Descriptor (WLD) algorithms. The Fisher discrimination ratio (FDR) feature selection algorithm was also used for these texture features. In addition to the texture properties, four morphological features were also extracted. Finally, SVM was applied to classify all these features. At the end of the study, images with YCbCr color space were classified via SVM with 98.1% success.

Some studies that classify date fruit based on deep learning are as follows: Altaheri et al. (2019) proposed a deep learning-based date fruit classification application for date fruit harvesting robots. In that study, date fruit clusters were classified according to their types, maturity and harvest status. The dataset, which includes more than 8000 date fruit cluster images, was created from the date palm garden. For classification, pre-trained AlexNet and VGG-16 CNN models were used for fine-tuned transfer learning. As a result of classification, the most successful results were obtained with VGG-16. VGG-16 provided %99.01, %97.25 and 98.59% accuracy for fruit type, maturity and harvest decision, respectively. Hossain et al. (2015) developed a study utilizing 5G and cloud technology for date fruit classification. For this, the images captured with a smartphone were uploaded to a cloud system via 5G and the date fruit type was determined. Pre-trained and fine-tuning CaffeNet CNN model was used for classification. In that study using 1000 date fruit images and four different date fruit types, a classification accuracy of 99.24% was achieved. Nasiri et al. (2019) presented a deep learning-based method to distinguish between healthy and defective date fruit and determine its maturity level. A dataset containing more than 1300 images and 4 different classes was created and classification was performed with pre-trained and fine-tuning VGG-16. As a result, an overall classification success of 96.98% was obtained. Faisal et al. (2020) conducted a deep learning and machine learning-based study to predict date fruit type, maturity level and weight, to develop an intelligent harvest decision system. Date fruit images were collected from the Center of Smart Robotics Research. For date fruit type and maturity level, four different CNN models (ResNet, NASNet, VGG-19 and Inception-V3) were used, while palm weight estimation was estimated with SVM. Maximum accuracy values of 99.175%, 99.058% and 84.27% were obtained for date fruit type, maturity level and weight, respectively. Pérez-Pérez et al. (2021) compared the performance of eight different CNN models (VGG-16, Inception V3, ResNet-50, VGG-19, ResNet-101, AlexNet and ResNet-152) for the classification of Medjool, the mature date fruit variety. The effects of five different hyperparameters (learning rate, the number of epochs, the number of layers, the optimizer and the mini-batch size) were also included in this comparison. As a result of the comparison, using the VGG-19 model with 128 batches, 0.01 learning rate and Adam optimizer, the best performance was obtained with 99.32% accuracy.

CONCLUSIONS

This investigation aimed to classify five Moroccan varieties of date fruits with five different CNN models: ResNet50, ResNet18, GoogleNet, MobileNetv2 and DenseNet. In terms of conclusion, the results showed that the application of current CNN models is a powerful tool for the classification of date fruits. Comparative analysis demonstrated that the most successful discrimination is achieved with MobileNetV2.

This CNN model was used as a feature extractor into a designed LSTM architecture to increase the accuracy of classification. In addition, the LSTM architecture, which contained selected features with fewer features, provides more successful discrimination than the original features. Thus, the 5-label 'Mejhoul' is the most successfully classified variety, distinguished with 100% accuracy by all other models except MobileNetV2.

Considering the obtained classification rates, the proposed method can be applied to automatically distinguish different varieties of date fruits with fast and high accuracy discrimination.

Further studies must be performed in the objective of applying the proposed methods to other date fruit varieties and to different agricultural products for proving the robustness of these artificial intelligence based-approaches.

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