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Date Fruit Varieties Identification Using Convolutional Neural Networks: A Comparative Study

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Abstract

Date fruit is one of the most important economical and cultural agricultural crops in the Middle East that plays a critical role in trade and food sustainability. These merits have attracted increasing interest from researchers and the food industry to improve food sustainability. The advent and integration of computer vision and artificial intelligence (AI) technologies have rapidly accelerated the progress in the development of automated classification, quality assessment, and grading for date fruits. This study offers an inclusive comparative analysis for ten pre-trained convolutional neural network (CNN) models used to classify fifteen different date fruit cultivars. The dataset obtained from two publicly available datasets. They contain images of cultivars from Saudi Arabia and Pakistan. The images are first preprocessed to enhance their quality, segmented, augmented to overcome the imbalance problem, standardized, and normalized to be fed then to the CNNs. Transfer learning was applied to fine-tune the pre-trained models using MATLAB 2023a software package. The performance of models were evaluated based on the overall accuracy, per-class accuracy, training time, execution time, and average inference time per image. Results showed that DarkNet-50 achieved the highest accuracy (99.33%), while MobileNet-V2 and ShuffleNet provided the best balance between accuracy and efficiency, hence they are well-suited for real-time or embedded applications.

1. Introduction

Date fruits have economical and cultural importance in the Middle East and North Africa region. They are considered to be a vital food sources and play an important role in agricultural markets due to their nutritional value. Furthermore, dates have historical, religious, and social implication in addition to their contribution to the regional and global food security. There are approximately 100 million date palm trees worldwide, with 62 million located in the MENA region [1], and around 600 distinct date varieties exhibiting diverse characteristics [2]. Thus, dates have gained special consideration from researchers and the food industry as part of sustainability efforts. Scientific research concerned with date fruits encompasses six primary tasks: variety identification or classification, quality grading, ripeness assessment, pest and disease identification, surface defect detection, and automated sorting.

Classification and grading of date fruits are of high importance from agriculture, commerce, nutrition, and conservation points of view. As it is well known that appropriate classification will lead to enhanced agricultural practices and improved harvest and quality through suitable variety selection. On the other hand, accurate identification is commercially central through facilitating market differentiation and allowing consumers to be aware of the available varieties and their nutritional value. Moreover, classification plays an important role in ecological preservation, avoids the extinction of rare varieties, and supports breeding programs intended for developing disease-resistant and high-yield cultivars. Therefore, a precise classification and grading systems for dates are of great importance for sustainable food resources by improving agricultural efficiency and food security.

The process of classification and identification of date fruit varieties usually includes a series of complex steps that integrates both traditional and modern techniques to ensure both precision and uniformity. It generally requires visual inspection, moisture content assessment, and texture analysis. The visual examination consists of the inspection of dimensions, morphology, color, and surface characteristics of the date fruit. In addition to that, attributes such as elongation, roundness, and wrinkling are also inspected to identify various cultivars and grading categories. Moisture content assessments categorize date fruits based on their hydration levels as soft, semi-dry, or dry. Moisture content assessments would then identify the longevity, flavor profiles, and applications in food processing. Finally, texture analysis evaluates attributes, including ripeness, surface quality, and defects, thereby supporting accurate grading and market differentiation [3].

The above-mentioned processes employ methodologies ranging from manual sorting techniques to those of sophisticated levels. Manual classification usually relies on human inspection and some sensory analysis. In this approach, laborers visually inspect and then assess date fruits to categorize them into soft, semi-dry, or dry based on moisture levels and firmness. They also assess the color and surface to identify imperfections such as wrinkles, cracks, or pest damage that affects the quality. Furthermore, dates are sorted through the variations in color, from golden yellow to deep brown, together with seed size and pulp-to-seed ratio. Another semi-manual inspection that utilizes sensory analysis is the tactile inspection, which is used to provide insights into freshness and maturity. In this test, mild compression is applied for each sample to determine firmness and adhesive properties. In spite of manual inspection is labor-intensive and time-consuming, still this classification methodology remains predominant in traditional markets and small-scale agricultural operations.

With the advent of computer vision systems, image processing techniques, and most recently the escalating advances in intelligent systems, the demand for efficiency and uniformity has increased. Therefore, many food producers nowadays are shifting towards automated systems that integrate computer vision and AI technologies in agricultural food grading and sorting systems to enhance or replace traditional methods. These new technologies are also being adopted in the transformation of the date fruit industry to automated classification based on size, shape, pattern, texture, and defect detection. This technical progress will certainly improves efficiency, uniformity, and accuracy, hence reducing dependence on manual sorting and minimizing human error. Additionally, AI-based systems greatly overcome human limits in identifying defects, maturity, and moisture contents, thus this will ensure that only superior quality dates reach the market. Consequently, such systems will greatly improve processing speed, increases yield, and improves overall product quality in the date industry [4].

During the last decade, AI systems have gradually adopted machine learning (ML) and deep learning techniques in agricultural applications. In the field of date fruit inspection, traditional ML techniques such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Random Forests, and Decision Trees have been employed. As is well known, ML techniques require the collection of well preprocessed datasets of images and sensor data. These datasets are analyzed to extract features either manually or using statistical techniques. Feature extraction assist in classify appropriate attributes such as size, shape, color, texture, and surface defects [5–8]. Generally, ML methods depend on handcrafted features thus, they are often limited by their ability of generalization. Moreover, their performance inclines with large-scale or highly imbalanced datasets. Conversely, deep learning techniques, especially CNNs, can analyze large datasets of images, automatically extract complex patterns and features to distinguish different varieties, quality and grades. Therefore, the aim of this study is to conduct a comprehensive assessment of the performance of ten widely used CNN architectures under an integrated preprocessing and training framework, by considering datasets taken under different imaging conditions. The study aims to analyze each model in terms of accuracy, response and generalization. The comparison not only highlights trade-offs between accuracy and efficiency but also provides real guidance for applying CNN-based classification systems in agricultural and industrial settings. While newer architectures such as Vision Transformers and ConvNeXt show great potential, the emphasis in this work is on recognized CNNs models that remain to serve as reliable standards in agricultural applications, ensuring reproducibility and offering a solid foundation for future work that builds on more advanced models.

2. Related Work

Due to the wide variety of date types, each with different characteristics such as color, shape, and texture, the identification process for date fruit variety is a complex task. Nevertheless, recent progress in computer vision and AI systems has noticeably improved the accuracy and the efficiency of such systems [4]. In general, these systems exploit various methods, such as MI and deep learning techniques, to identify and classify date fruits based on their visual and physical features. The use of classical MI techniques, such as SVM [5], Artificial Neural

Networks (ANN) [6], k-NN [7], and Logistic Regression [8], and many others, has been investigated in several studies. In this approach date fruits are usually classified based on their morphological features: color, texture, and shape. Although classical MI methods have shown an excellent classification rate in some cases, still they regularly lack the flexibility and adaptability that could be obtained when using deep learning techniques. In general, classical MI methods suffer from a number of problems, such as variations in lighting, angles, and environmental aspects that would significantly affect their classification accuracy. Furthermore, Classical MI methods generally require extensive preprocessing and feature extraction, such as Principal Component Analysis, which is a dimensionality reduction technique, to achieve optimal results [7]. On the other hand, deep learning techniques have been steadily developed to become a highly effective approach that has surpassed classical MI techniques, especially in applications that require the analysis of complex visual features such as agricultural product classification [9]. An example of such techniques is the CNN, which proved to have superiority in the field of image-based classification and quality assessment of agricultural crops [10]. CNNs have the distinctive feature that they automatically learn and extract visual patterns directly from raw image data, even under challenging conditions like varying illumination, occlusion, or background noise. In general, a CNN consists of several main layers that work together as shown in Fig. 1. A single layer in CNNs can be made from multiple components, each designed to perform a specific function. The principle operation and function of each layer is thoroughly explained in [11]. In general, CNN architecture can be classified into two major categories: custom networks and pre-trained networks. In the first category, the network is designed and developed from scratch using foundational components, while in the latter, well-established pre-designed CNN models such as VGGNet and AlexNet are adopted and modified to augment placement with specific research objectives.

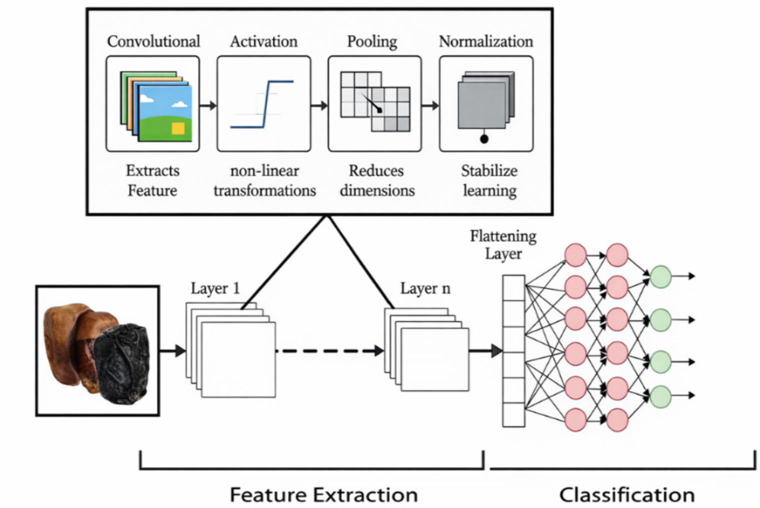

Fig. 1 *A typical CNN architecture*

Several studies have proposed custom CNNs for the classification and identification of date fruit cultivars. Hossain et al. [12] designed a CNN architecture that is integrated within an edge computing framework for smart city applications. The system allowed real-time classification of date fruits using a lightweight CNN installed at the edge to reduce latency. Though specific layer details were not revealed, the emphasis was on computational efficiency and consumer satisfaction. Their proposed model attained high accuracy in real-time environments and claimed to prove the feasibility of using CNN for classification in constrained smart infrastructure. In 2019, Magsi et al. [13] proposed the integration of feature extraction techniques with a custom CNN for identifying date fruit varieties. Their model consisted of five convolutional layers, each followed by ReLU and max pooling, and two fully connected layers. The model was trained with a dataset that contains images of different date cultivars and succeeded in achieving a classification accuracy of 98.3%. The authors underlined that the combination of traditional feature extraction, such as color and shape descriptors, with learned features by the CNN, enhanced the robustness by generalization across varying lighting and backgrounds. Raissouli et al. [14] collected their own dataset and applied CNNs for both grading and classification of date fruits. Although the details of the proposed model were not revealed, the authors focused on data variety and quality control of their model through the demonstration of grading of date fruits based on ripeness and physical defects. The study showed the achievement of high performance with minimal preprocessing. Alhamdan and Howe [15] developed their own custom CNN model that is composed of three convolutional layers, followed by dropout and dense layers. They collected their own dataset under the controlled environment of consistent lighting and background. The model achieved accuracy exceeding 95%, thus indicating that well-controlled imaging can enhance model reliability. Neji et al. [16] introduced a CNN model that examines both the fruit and the leaf images for cultivar identification. This multimodal input allowed the system to capture a wide range of morphological features. Their architecture consists of multiple convolutional and pooling layers followed by dense layers and optimized using a dropout layer. The authors reported high accuracy and confirmed the benefit of combining different plant parts for more robust classification. The CNN model proposed by Albarrak et al. [17] consists of five convolutional layers that merge data augmentation and batch normalization. The model was tested on an augmented dataset and achieved 97.8% classification accuracy. The study also emphasized the model's low computational footprint, making it deployable on mobile or embedded devices. Recently, Rybacki et al. [18] utilized residual connections and global average pooling in their model to increase learning efficiency and reduce overfitting. Their model was tested on their own high-resolution dataset and claimed to achieve over 98% accuracy. Finally, Maitlo et al. [19] introduced a CNN-based classification system trained on a newly collected dataset of date fruit images. Their custom model consists of four convolutional layers, each followed by ReLU and max pooling, and ends with dense layers and a softmax classifier. The model reached 96.7% accuracy with images of various environmental conditions and fruit orientations.

Faisal et al. [20] developed the Intelligent Harvesting Decision System using three pre-trained CNN models—VGG-19, Inception-v3, and NASNet—, which were modified to estimate and classify maturity level of date fruits. The system used a novel preprocessing framework to enhance the appearance of surface features that assist the system ability to differentiate between maturity levels. The system proved to achieve an average accuracy of 98.45% for the modified VGG-19 model. The same research group later expanded their system to be a multi-output system that can simultaneously identify date type, its maturity level, and its weight [21]. ResNet was also consider with the previous set of CNN models, in which all the models have a common convolutional feature extraction layers and then split into three heads for different tasks. The models were trained on a large dataset, and results showed that the ResNet attained the highest accuracy of 99.18% for date type identification and 99.06% for maturity level estimation. Alshammari [22] proposed a system that utilized Convolutional Radial Basis Network to select features from date images, and then a U-Net encoder-decoder model is used to classify their varieties. The dataset used for training the system contains 898 images for different seven date varieties. The authors claimed that their proposed model achieved high a high accuracy of 97%. Alhadhrami et al. [23] utilized transfer-learning approach and tested three pre-trained CNNs—ResNet-50, VGG-16, and AlexNet—to classify four common types of date fruits in the UAE. A dataset of 260 high-resolution images was used to train and test the models. The system was developed using MATLAB's Deep Network Designer. This study showed that the AlexNet model achieved the highest validation accuracy of 100%, while the VGG-16 model achieved the highest testing accuracy of 98.33%. It should be noted that this study highlighted the reliability of CNN models of achieving high classification accuracy even with a relatively small dataset. Raman and Subekti [24] adopted DenseNet-201 for identifying date varieties. They investigated three different settings, namely, freezing all pre-trained layers, retraining all layers, and using a hyperparameter-tuned model by partial layer retraining and optimization with Nadam. The DenseNet-201 with a tuned hyperparameter model achieved the highest accuracy of 99.39% when compared with other models such as ResNet-152V2, VGG, and MobileNet. Alavi et al. [25] investigated the use of five pre-trained CNN architectures, namely, SqueezeNet, GoogLeNet, EfficientNet-B0, ShuffleNet, and MobileNetV2. These models were trained and tested to classify five subcategories of Sukkari dates fruit under the same conditions. The study showed that the lightweight SqueezeNet architecture achieved an accuracy of 92% with the shortest training time. All these features led the authors to strongly recommend of using the SqueezeNet for date fruit classification. Latif et al. [26] also adopted transfer-learning approach by using lightweight CNNs such as MobileNet and InceptionV3, which are claimed to exhibit high accuracy-to-computation ratios. The authors overcome overfitting problem and improved model generalization by adding dropout layers and data augmentation. The best-performing model reached 95.8% accuracy. Ahammad et al. [27] developed a system for classifying date fruits using four CNN models: VGG-19, Xception, MobileNetV2, and DenseNet201, and proposed a hybrid model called DateNet which is a combination of both the MobileNetV2 and DenseNet201 models. The study assessed the DateNet model and found that it achieved the highest classification accuracy of 98.78%, thus, outperforming all other models. The model was deployed into a real-time mobile application using TensorFlow Lite and FASTAPI.

In addition to the two classical research approaches, i.e using custom and pre-trained CNN, special research studies some studies have different different approaches and extensions. These studies focus on three important aspects, real-time object detection, data augmentation and explainable deep learning. In first stream, Almutairi et al. [4] utilized different versions of YOLO object detection models to automate the detection and classification of nine date fruit varieties. The authors applied preprocessing, data augmentation, and bounding box annotation on a dataset of 1,735 high-resolution images. The study showed that the YOLOv8 model exhibits the best balance between accuracy and real-time performance. The model achieved the highest overall performance, with precision and recall rates of 0.991 and 0.99, respectively, and a mean average precision (mAP@0.5) of 0.994. The authors then deployed the best model in a mobile application that identifies date types and their sugar content from images. Syed et al. [28] employed YOLO-based object detection models for classifying date fruit varieties based on their external features. The study showed that the YOLOv9 model achieved the highest performance with

99.5% overall fitness, 98.68% precision, and 99.06% recall. Regarding data augmentation, Alajlan et al. [29] addressed the challenge that face almost all investigation due to the limited and imbalanced datasets They collected limited number of images for three Saudi date fruit varieties and utilized Deep Convolutional Generative Adversarial Networks (DCGAN) as a data augmentation tool. Two CNN models, Keras-based CNN and MobileNet, were evaluated limited dataset before and after the augmentation. The investigation showed that the accuracy for the MobileNet model increased from 83% to 88% after the utilization DCGAN augmentation, while CNN's performance dropped due to overfitting. Ibrahim and Elshennawy [30] also addressed the issue of limited and imbalanced datasets. They employed two data augmentation techniques namely, DCGAN and CycleGAN. Two CNN models were trained on the original, DCGAN-augmented, and CycleGAN-augmented datasets. Results proved that augmentation considerably improved classification accuracy, with the ResNet152V2 model to reach an accuracy of 96.8% on the CycleGAN-augmented dataset. Finally, Zaki et al. [31] suggested the integration of explainable AI (XAI) tools such as Grad-CAM with pre-trained ResNet CNN model to provide a transparent visualization tools that provide perceptions into which features were most relevant for classification. No major changes were made to the structure of the base CNN, only classifier layers were modified. The model was first fine-tuned using a labeled date fruit dataset, and then test to reached an accuracy of 96.9%.

3. Materials and Methods

This section presents the methodological framework developed in this study to evaluate and analyze the performance of very well-established CNNs, which are available in Matlab's Deep Learning Toolbox, for classifying date fruit varieties. The methodology focuses on three main stages, namely, the selection of appropriate dataset, preparation and preprocessing images that would be used for training, and finally the description and selection of the CNNs models under investigation. Each stage was designed to ensure that the results can be repeated, are reliable, and provide a fair comparison between the different CNN models.

3.1 Dataset

In order to assess the performance of the selected CNN models investigated in this paper to classify date fruit varieties, several publically available datasets were considered. Only two of these dataset were considered since they are well-recognized in the research community, and contain well-organized image collection for a wide range of date fruit varieties with adequate samples. The first dataset contains 1,658 high-resolution images for nine Saudi Arabian date varieties, namely, Ajwa, Galaxy, Medjool, Meneifi, Nabtat Ali, Rutab, Shaishe, Sokari, and Sugaey [32]. The Images provided in this dataset were captured by a Canon EOS 550D DSLR camera. To ensure low noise and lighting variability only a LED ring light is used, and the date samples were placed on a raised platform against a white background with a constant camera distance of 8 cm. Such a setup ensures a controlled condition, for all the images and hence making the dataset, a reliable basis for evaluation and the obtained results would reproducible and comparable with earlier research. The second dataset contains 1,399 high-resolution images representing for seven date varieties from Pakistan and Saudi Arabia, namely, Ajwa, Aseel, Muzafati, Zahidi, Kalmi, and Khorma [33]. The collected images in this dataset were also captured under controlled conditions by using a Vivo S1 AI smartphone placed at a fixed distance of 15 cm between the camera and the sample. The authors in [33] claim that all the samples included in the second dataset were taken under controlled conditions with uniform illumination and background noise reduction. Nevertheless, a variation in the distance and images' backgrounds were noticed during the inspection of all the samples in this dataset.

After careful examination all the images in the two datasets, it was found that the images in first dataset are of high-resolution, thus even fine visual details between closely related date fruit varieties are very clear and distinguishable. While the diversity in fruit origin, smartphone acquisition setup, and the inconsistency of the images in the second dataset would lead to a motivating challenge for researchers to utilize this dataset in testing CNN robustness across varying conditions. Finally, it should be stated that after preprocessing the merge of two datasets would provide distinct and valuable source for date fruit classification. Table 1 lists the number of samples for each type, and Fig. 2 shows a sample of each variety after the segmentation process, which will be discussed in the next section.

3.2 Pre-Processing

As mentioned in the previous section, the two datasets have several differences and variations between the captured images. Therefore, prior to training CNN models, all images need a special pre-processed framework to eliminate these variations and to ensure the consistency and comparability in order to obtain an optimal model performance. The suggested framework, as shown in Fig. 3, consists of four stages, namely, image segmentation, data augmentation, image standardization and resizing, and dataset splitting. These preprocessing modules are designed to ensure that all input images meet the requirements of the models' training and testing through the preservation of the critical visual features and patterns that are needed for accurate classification.

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Fig. 2 *Samples of different date fruit verities; top row before preprocessing, bottom raw after preprocessing and segmentation*

Table 1 *Comparative summary of two publicly available date fruit image datasets*

Feature	Dataset 1	Dataset 2
Title & Year	Date fruit image dataset in controlled environment, 2022	Date Fruit Dataset, 2023
Total images	1,658 high-quality JPGs	1400 medium-quality JPGs
Date varieties	9 types	7 types
Image capture	Controlled environment	Controlled environment
Camera	Canon EOS 550D DSLR camera	Vivo S1 AI smartphone
Image Clarity	Very Good	Good

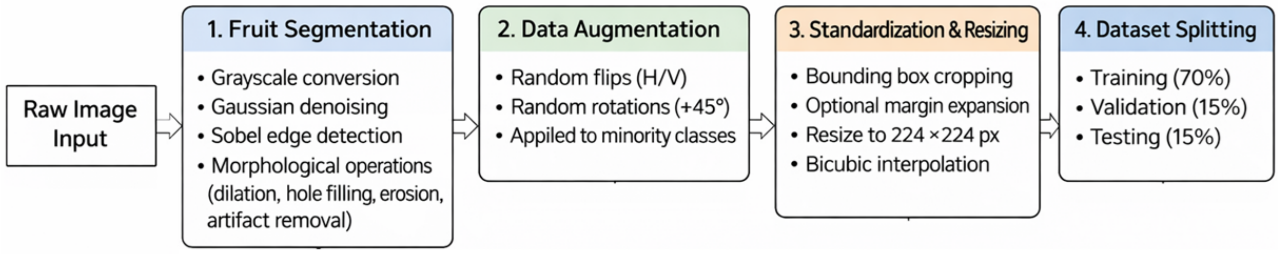


Fig. 3 *Overview of the image preprocessing pipeline for date fruit classification*

As can be noticed from figure 2, date fruits usually occupy only a part of the image frame, while the rest of the image shows the background and shadows. Since the images were captured using different cameras, camera-to-subject distance, the color of the background, and the noise level, object filtering and segmentation are then required. Segmentation in this framework involved isolating the region of interest, i.e., the part of the image that only contains the object. This extraction can be done by outlining object borders and then efficiently isolating the object from the background, without affecting the quality of the image. A simple yet effective image segmentation algorithm that combines edge detection and morphological operations was developed in this study. The process began by converting raw images from RGB to grayscale images. Next, Gaussian filtering is then applied to remove noise and to enhance the clarity of objects' boundaries. To isolate and then identify distinct objects in the image, Sobel edge detection was then applied to extract high-contrast contours for these regions. Nevertheless, this set of operations does not always extract the date fruit boundaries, but some of the regions that contain noise in the background and shadows would also appear in this stage. To remove these unwanted regions and some noise that could appear in this stage, a sequence of morphological operations is applied to obtain a clear binary segmentation mask just for the date fruit. The morphological operations include dilation to connect disjointed edges, hole filling to extract object interiors, erosion to refine shapes, and small object removal to remove artifacts. This sequence of operations was found very effective and robust pipeline for the segmentation of the date fruits from the background and overlapping objects, even under varying illumination or occlusion. Fig. 2 presents representative samples of the segmented images.

To ensure a diverse dataset with a sufficient amount of training data with expressive features, data augmentation was applied to the segmented images. Data augmentation improves CNN model generalization by exposing the CNN to different styles of the same image. It also improves model robustness by ensuring the CNN can classify different date fruit samples under challenging conditions. Finally, augmentation prevents memorization and endorses learning of general features, thus reducing overfitting. Together, these factors would significantly enhance the performance of CNN models. Because of the variation in the number of samples between different date classes, the augmentation was only applied to the classes with low sizes. This strategy helps in balancing the training set, minimizing the bias toward classes of high size, and reducing the overfitting problem. In this study, only two lightweight augmentation techniques were applied, namely, random horizontal and vertical flips and rotations within ±45°. These two methods were chosen for their computational efficiency and their ability to preserve the main content of the images when spatial orientation is applied to the image.

After completing segmentation and augmentation, the preprocessed and generated each date fruit, as an object, was extracted using automatically generated bounding box from the binary segmentation mask. These cropped images then subjected to standardization first and then resizing. Since images are captured and subjected to different conditions, then they may contain widely varying pixel intensity values. The standardization assure that all input images have consistent characteristics hence they will learn effectively and their prediction accuracy will be improved. These standardized images are then resized to a predefined dimension (224×224×3) using bicubic interpolation to balance spatial fidelity and computational efficiency.

Finally, for model training and evaluation, the dataset was split into a training set of 70%, a validation set of 15%, and a testing set of 15%. The training set was used to train the models, the validation set is used for hyperparameter tuning and performance monitoring, while the testing set is solely used for final evaluation to measure generalization on hidden data. To prevent data leakage, augmented images were included only in the training subset.

3.3 Convolutional Neural Networks Architectures

In this study ten CNN models, namely, AlexNet, VGG-19, GoogleNet, ResNet-50, Inception-v3, SqueezeNet, MobileNetV2, ShuffleNet, EfficientNetB0, and DarkNet, have been investigated to identify different date fruit varieties. These models were chosen because they offer a comprehensive range of CNN design philosophies, have different network depths and computational complexities, and have different approaches to feature extraction. These CNN models are part of a series of models that were suggested and designed for the "ImageNet Large Scale Visual Recognition Challenge." ImageNet Large Scale Visual Recognition Challenge, for short (ImageNet / ILSVRC), is an annual competition in computer vision for benchmarking and evaluating the performance of computer algorithms in the fields of image classification, object detection, and object localization. Some of the aforementioned CNN models won this competition, while some were found to be within the top five models in terms of accuracy and inference time. In general, these models vary in depth, efficiency, and ability to learn complicated patterns in images. The architecture of these models ranges from small and compact architectures that are designed for execution speed to very large or deep models designed to capture complicated patterns. Therefore, this comparative selection is believed to enable the identification of the best and most effective architecture(s) to distinguish and extract distinctive visual features and differences among date cultivars.

Table (2) illustrates a summary comparison of the selected CNN models in terms of the depth of the model (layers), learnable weights and biases (parameters), required storage space to represent the model (model size), and the key characteristics and advantages of each model (features). As it can be noticed from the table, each model has its pros and cons. For example, AlexNet and VGG-19 provide initial visions into classical deep CNN architectures that are constructed from sequential convolutional layers, while GoogleNet and Inception-v3 present inception modules that can extract different spatial resolutions and features very efficiently. On the other hand, networks like ResNet-50 integrate residual learning modules to resolve the vanishing gradients problem in deep networks. SqueezeNet, MobileNetV2, and ShuffleNet all have lightweight architectures that are designed and optimized for computational speed and to overcome low resources, as in mobile applications. Finally, EfficientNetB0 architecture utilizes multiple scaling to compromise between depth, width, and resolution, and DarkNet, which is the backbone of the YOLO models, was designed and optimized to offer a fast and powerful feature extraction framework that would fit in real-time applications.

By comparing such a varied range of CNN models, this study aims to determine which model would effectively extract and learn distinctive variations in texture and shape for different date cultivars. The assessment also inspects how efficiently each model maintains robustness and generalization under different imaging conditions, such as variation in lighting, background, and sample orientation. This comprehensive study also highlights the compromise between accuracy and efficiency. Furthermore, it also provides valuable understanding on the selection of the optimal CNN model for practical agricultural image classification tasks. It should be noted that newer approaches and models have been recently introduced, such as Vision Transformers and ConvNeXt show countless potential. These newly proposed algorithms are not considered in this study due to their recent introduction to the research community and have not yet widely utilized or tested in agricultural and related.

Table 2 *Summary comparison of popular CNN architectures*

CNN Model	Year	Layers	Parameters (M)	Model Size (MB)	Features
AlexNet [34]	2012	8	60	~240	Fast and simple; good for beginners and small-scale image tasks.
VGG19 [35]	2014	19	143	~548	High accuracy, but large and slow; ideal for fine-tuning on powerful systems.
GoogleNet [36]	2014	22	7	~27	Efficient and compact; excellent trade-off between speed and accuracy.
ResNet-50[37]	2015	50	25.6	~98	Deep and powerful; handles vanishing gradients well via residuals.
Inception-V3[38]	2015	48	23	~89	Accurate and multi-scale, but needs larger input size and is slower.
SqueezNet[39]	2016	18	1.25	~4.8	Ultra-lightweight; great for edge devices or when storage is limited
MobileNet-V2[40]	2018	88	3.4	~14	Optimized for mobile/embedded AI; strong speed-size-accuracy balance
ShuffelNet [41]	2018	50	5	~10	Designed for speed and efficiency; best for mobile and low-power systems
EfficientNetB0 [42]	2019	237	5.3	~20	Modern architecture; delivers high accuracy with minimal computational cost
DarkNet [43]	2020	50	25	~90	Compact YOLO backbone; good for real-time detection, imported via ONNX

4. Results and Analysis

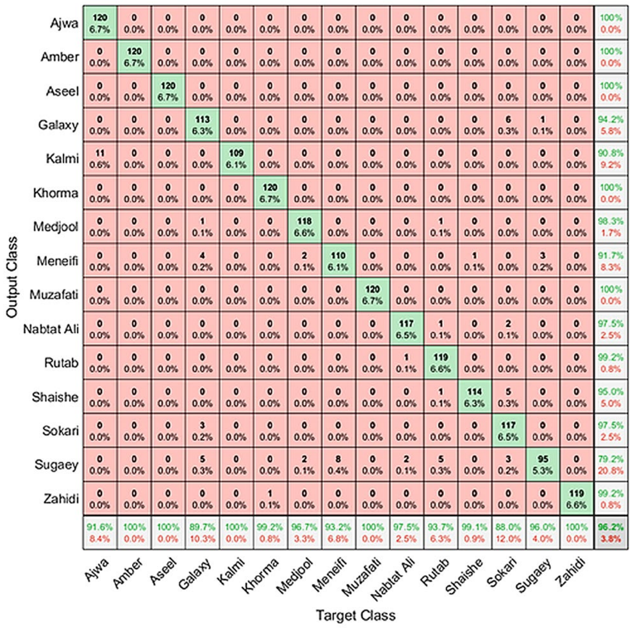
This section will present an inclusive insight for the training, testing, and performance evaluation of the ten selected CNN used for the identification of date fruit cultivars. Models listed in Table 2 were adjusted and modified to be trained and tested using the combined dataset, which includes fifteen date varieties, namely Ajwa, Amber, Aseel, Galaxy, Kalmi, Khorma, Medjool, Meneifi, Muzafati, Nabtat Ali, Rutab, Shaishe, Sokari, Sugaey, and Zahidi. The objective was set to compare the classification accuracy and computational efficiency in terms of training and inference time while ensuring consistency for all the classes. All the investigated models were adopted from the MATLAB 2023a Deep Learning Toolbox. These models have been pretrained for the ImageNet dataset, where their parameters—learnable weights and biases—have already been set based on the aforementioned application. Therefore, a fine-tuning was required to make these models suitable to identify the date fruit dataset images, wherein the input image layers and some of the final output layer have been adjusted or replaced to fit with the requirement of the new task. These modified models were then retrained using the training dataset. It should be mentioned here that data augmentation was only applied to the training and validation subsets, while the 15% testing subset included original non-preprocessed images. This methodology in the preparation of the sub-datasets is believed to ensure the prevention of data leakage, since no augmented version of any date fruit sample will appear in more than one subset. Furthermore, a balanced sampling was strictly implemented to guarantee that each split, i.e., testing, validation, and testing subsets, has a balanced representation of all date fruit classes. An Intel Core i7 12th Gen 2.80 GHz laptop with 36 GB RAM and a 64-bit Windows 11 operating system was used to train and test all the models. The size for all the input images was standardized to 224×224×3 pixels, and the Stochastic Gradient Descent with Momentum algorithm was used for optimization of learning, with a rate set to 1×10−3 and a momentum factor of 0.9 to accelerate gradient vectors in the correct directions and reduce oscillations. The training process was executed over 10 epochs with a batch size of 64. Data shuffling was utilized at the start of each epoch to certify good generality. Finally, the validation process was set to initiate every 100 iterations, with a subset of images representing 15% of the total images used for this purpose.

With these well-defined hyperparameters and parameters, evaluation and assessment of the models were focused on their prediction performances, which are measured using the following metrics:

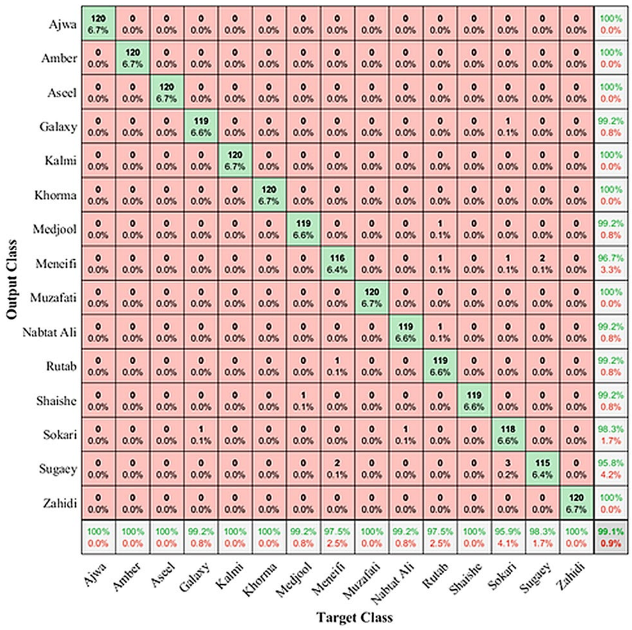
- Overall Accuracy
- Per-Class Accuracy
- Training Time
- Execution Time for 1800 samples
- Average Inference Time per Image

The overall accuracy is defined as the ratio of the number of correct predictions to the total number of input samples. The factors that are usually used to compute the accuracy are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These are factors that can be deduced directly from the confusion matrix. The confusion matrix is used to visualize the model's classification performance by illustrating the number of correct and incorrect predictions for actual and predicted classes. Equation 1 is usually used for the overall accuracy, and Fig. 4 shows two samples of the confusion matrices for the tested models.

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



AlexNet



(a) MobileNet-V2

Fig. 4 *Samples of the confusion matrices, left AlexNet, right MobileNet-V2*

Based on the results presented in Table 3, the comparison between the performances of the ten CNN models clearly shows that the DarkNet-50 architecture has attained the highest overall accuracy of 99.33% and is then narrowly followed by VGG19 with an accuracy of 98.88%, ShuffleNet with 98.78%, and MobileNet-V2 with 98.72%. The high accuracy attained by the DarkNet-50 is attributed to its deepness, i.e., number of layers, and the use of residual connections. These two factors greatly influence feature extraction and the generality of the model. Likewise, the high accuracy of the VGG19's architecture can be attributed to its depth, which permits robust hierarchical feature extraction capability. On the other hand, models such as ShuffleNet and MobileNet-V2 have a low number of layers but are designed to achieve high efficiency with special techniques. MobileNet-V2 utilizes the depthwise separable convolution strategy, which breaks the classical convolution process into two simpler steps, namely, depthwise convolution and pointwise convolution. ShuffleNet has a different strategy for its design that is called channel shuffling, which facilitates feature exchange and interaction between different channels. Although AlexNet and SqueezeNet have achieved comparatively lower accuracies, of 96.17% and 95.67% respectively, and this can be attributed to their simple and shallow structure. Nevertheless, their accuracy level is excellent when considering their compact structures. Overall, all the investigated CNN models have attained remarkably high accuracy and it is believed that this can be attributed to the presentation and preprocessing of the dataset.

The per-class accuracy is an important performance measure that is used in multi-class classification to assess how accurately the model predicts each class. Formally, it is defined as the ratio of the number of exact predictions for a given class to the total number of samples of that class. Usually the per-class accuracy is calculated by iterating through the test subset to count the correct predictions for each class. This can be deduced efficiently by means of the confusion matrix, in which the diagonal elements denote the count of correct classifications and the sum of other values in the corresponding row represents total samples per class. The pre-class accuracy also provides a detailed assessment of the model's performance for all classes, and this helps in identifying areas for targeted improvement. Table 4 presents different valuable insights concerning the per-class accuracy for each model. This evaluation offers a reliable model-specific measure for the identification of the fifteen classes. As expected, the DarkNet-50 demonstrated excellent classification accuracy across all the classes. This in turn leads to a conclusion that the DarkNet-50 model exhibits strong generalization and feature perception capabilities. Similarly, ResNet-50 and MobileNet-V2 also attained a high per-class classification accuracy; some exceeded 99% for most of the classes. It should be noted that some classes, like Ajwa, Aseel, and Muzafati, were identified with an accuracy of 100% by all the models. This implication suggests that these varieties have clear and distinctive visual features that can be easily recognized and learned by the CNN models. On the other hand, some other varieties like Sugaey and Meneifi have attained the lowest per-class accuracies (79.2% for Sugaey with AlexNet, 83.3% for the same type with SqueezeNet, and 83.3% for Meneifi with SqueezeNet). Such results imply that shallow networks like SqueezeNet and AlexNet would not be able to provide an acceptable accuracy rate, above 90%, due to their lightweight architecture and simple design that would prevent them from the extraction of the features required for the classification, or possibly due to the imperfection of the preprocessing of the images. Based on the aforementioned observations, it can be stated that CNN models designed with a high number of layers and with residual connections or with adaptive weight adjustment mechanisms can capture miniature features; hence, these models would most likely have high overall and per-class accuracies.

Table 3 *Performance comparison of CNN models*

Model	Accuracy (%)	Training Time	Execution Time (1800 images)	Avg. Inference Time
AlexNet	96.17	87 min	38.65 sec	0.0215 sec
VGG19	98.88	786 min	182.74 sec	0.1015 sec
GoogleNet	97.06	341 min	79.21 sec	0.0440 sec
ResNet-50	98.73	625 min	159.12 sec	0.0884 sec
Inception-V3	97.56	647 min	138.05 sec	0.0767 sec
SqueezeNet	95.67	132 min	71.81 sec	0.0399 sec
MobileNet-V2	98.72	440 min	74.42 sec	0.0413 sec
EfficientNet-B0	97.61	550 min	86.86 sec	0.0482 sec
DarkNet-50	99.33	880 min	333.31 sec	0.1852 sec
ShuffleNet	98.78	201 min	73.62 sec	0.0409 sec

Table 4 *Per-class accuracy (%) of CNN models across fifteen date fruit varieties*

Model	Ajwa	Amber	Aseel	Galaxy	Kalmi	Khorma	Medjool	Meneifi	Muzafati	Nabtat Ali	Rutab	Shaishe	Sokari	Sugaey	Zahidi
AlexNet	100%	100%	100%	94.2%	90.8%	100%	98.3%	91.7%	100%	97.5%	99.2%	95%	97.5%	79.2%	99.2%
VGG19	98.3%	100%	100%	97.5%	99.2%	100%	98.3%	98.3%	100%	98.3%	99.2%	99.2%	95.8%	99.2%	100%
GoogleNet	100%	100%	100%	85%	100%	100%	95%	90.8%	100%	97.5%	97.5%	100%	92.5%	97.5%	100%
ResNet-50	100%	100%	100%	97.5%	100%	100%	100%	91.7%	100%	100%	100%	100%	96.7%	96%	100%
Inception-V3	100%	100%	100%	95%	100%	98.3%	97.5%	90%	100%	99.2%	99.2%	98.3%	95%	90.8%	100%
SqueezeNet	100%	97.5%	100%	98.3%	90%	100%	100%	83.3%	100%	94.2%	95.8%	97.5%	95.8%	83.3%	99.2%
MobileNet-V2	100%	100%	100%	99.2%	100%	100%	99.2%	96.7%	100%	99.2%	99.2%	99.2%	98.3%	95.8%	100%
EfficientNet-B0	99.2%	100%	100%	97.5%	98.3%	100%	96.7%	91.7%	99.2%	97.5%	98.3%	99.2%	95%	91.7%	100%
DarkNet-50	100%	100%	100%	100%	98.3%	100%	99.2%	100%	100%	100%	99.2%	100%	96.7%	96.7%	100%
ShuffleNet	99.2%	99.2%	100%	97.5%	97.5%	100%	99.2%	99.2%	100%	97.5%	100%	99.2%	99.2%	99.2%	100%

The third metric used to assess the models is the training time, which represents the time required for the model under investigation to converge its weights and achieve high accuracy and minimum loss when tested with both the testing and validation subsets. During the training period the model learns distinctive patterns and features from the testing sub-dataset. During this process, the weights and biases are adjusted by minimizing a loss function. The duration needed for this stage depends on a number of factors, such as network depth and complexity, dataset size, number of epochs, batch size, and the hardware used. Larger and more complex models trained with a large-scale dataset would certainly demand more computation resources and time. Nevertheless, with modern computing platforms that are equipped with GPUs or TPUs, the training time can be significantly reduced. During the training stage, the process goes through a number of validation interrupts. The purpose of these validation checks is to tune the hyperparameters, which include the learning rate, batch size, and dropout rate. During the validation phase, the system uses the validation sub-dataset and, in general, will monitor the performance of the model during the training. MATLAB's Deep Learning Toolbox provides a tool to monitor the accuracy and loss function variation during the training session for any model. Fig. 5 shows a few examples of the testing and validation accuracy during the training duration. On the other hand, the execution time measured during the final testing or validation stage is used to measure the required time needed by the trained CNN model to process and classify the non-augmented testing dataset. In this study, 1,800 samples were used for this task. This execution time is also influenced by model density and the computational resource. In general, the consideration of this performance metric is believed to provide a valuable measure of the efficiency and suitability of models when deployed in large-scale and real-time applications. Finally, the average inference time per image denotes the time needed by a trained CNN model to classify a single sample. The calculation of this metric is simply obtained by dividing the total execution time, already obtained from the previous calculation, by the number of images, which is 1,800. This performance metric is believed to be a vital measure in assessing model suitability and efficiency when deployed in real-time or embedded applications. A comparison of all the investigated models in this study in terms of overall accuracy, training time, execution time, and inference time is given in Table 3. While Table 4 provides a comparison between the models in terms of per-class accuracy. The computational performance of all the models were compared in terms their training and inference times. Results presented in table 3 show that there is a wide variation between the models. As mentioned previously that both training and inference times depend on the depth, complexity and parameters size of the model. Therefore, it would be obvious that models such as DarkNet-50 and VGG19 take comparatively longer training and execution times, while lightweight models such as SqueezeNet, ShuffleNet and MobileNet-V2, would be faster to train and need shorter inference times.

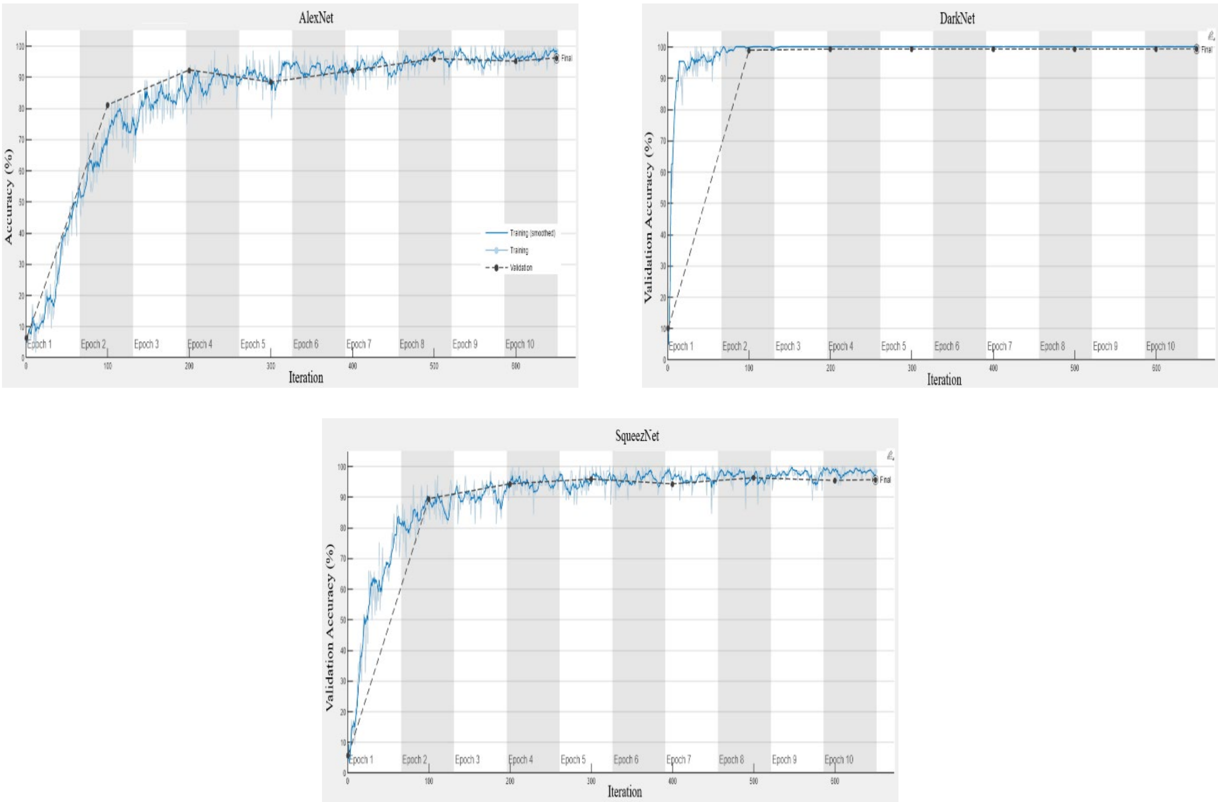


Fig. 5 *Samples of the training and validation plots for CNNs*

5. Conclusions

The classification and grading of date fruits is considered as vital process for both producers and industry to maintain and ensure high quality and market value. Therefore, the investment in developing efficient and accurate classification and grading systems is considered an essential objective for the future for advancing and sustainable food industry. This study focuses on the performance assessment and effectiveness of CNNs in the classification process of date fruit varieties. The literature survey conducted in this study shows that previous studies in this filed have investigated only on one or few CNN models. In contrast, this research have examined ten well-established and tested pre-trained models in terms of their classification and computational performances under a unified framework using two different datasets taken from different sources and with different acquisition sources. Such a wide and comprehensive and systematic comparative analysis is believed to provide a practical and fair assessment for a wide spectrum of CNN models that have been initially designed with different strategies. As a consequence of this objective, the main contribution of this research lies provide a clear and solid base for future research to assist as a guidance for the agricultural industry as it transfers to the adaptation of intelligent and smart classification and grading technologies.

As a part of this investigation, two publicly available datasets were combined to present images for fifteen date varieties, which were used to assess the selected CNN models. An integrated preprocessing framework was proposed to segment, augment, and standardize the images, ensuring uniformity and equality in the training phase for all the models. To assess and evaluate the accuracy and computations performance, each model was finely modified to fit the intended application and then tested under the same conditions and settings. Based on the obtained results, the analysis revealed that models such as DarkNet-50 and VGG19, which have deep structure, can always attain a high classification accuracy, reaching 99% for some models. Nevertheless, this high accuracy rate for deep models is combined with a decrease in the computational performance and resource, i.e., training and inference time and the computer resources. On the other side, lightweight models such as AlexNet and SequeezNet have much better computational performance but at the cost of relatively lower accuracy. To reach a compromise between these two wings, models such as MobileNet-V2 and ShuffleNet are found to offer an acceptable balance between accuracy and efficiency through the achievement of a high accuracy level with notably low training and inference times. This spectrum of results provides a wide and clear insight on the optimal choice of CNN architecture being contingent on the proposed application. For example, in research or industrial applications the priority will go in favor of maximum accuracy; thus, deeper models with residual connections will be the preferable option. While for real-time and embedded applications, with limited computational resources, lightweight models will usually be adopted. The overall findings of this study stress that, in the field of agricultural crop classification, the deployment of CNNs needs a careful balance between model complexity and application requirements.

Finally, in order to further improve the performance and efficiency of classification and grading systems, future research could explore ensemble learning, attention-based methodologies, and the use of sort of datasets, such as texture or hyperspectral information. Moreover, recent advances in CNN–Transformer hybrids, such as ConvNeXt and Swin Transformer, need to be included in future studies to lead to greater improvements in classification performance and paving the way toward next-generation AI-driven systems.

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Conflict of Interest

The author declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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