# Date fruit classification using CNN and stacking model

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**ABSTRACT**

In North Africa and the Middle East, the date is the most popular fruit, with millions of tons harvested annually. They are a crucial component of the diet due to their exceptional content of essential vitamins and minerals, which confer a high nutritional value. The ability to accurately identify and differentiate between date varieties is therefore of paramount importance in agriculture. It is crucial for improving agricultural practices, ensuring harvest quality, and contributing to the economic development of date-producing regions. In this paper, we propose a hybrid method for classifying date fruit varieties based on two stages. In the first stage, we select the two best-performing pre-trained models from six experimented deep learning models, and we concatenate the feature maps extracted from these two models. In the second stage, we apply different classification methods, including artificial neural networks (ANN), support vector machines (SVM), and logistic regression (LR). The performance achieved by these methods is 97.22%, 98.46%, and 99.07%, respectively. Then, with the stacking model, we combined these methods, and the performance result was increased to 99.38%. This result demonstrates the effectiveness of the hybrid model for identifying date fruit varieties.



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## 1. INTRODUCTION

In recent years, the rapid advancement of artificial intelligence (AI) has led to significant transformations across multiple sectors, including agriculture [1]. AI has emerged as a critical tool for addressing complex agricultural challenges, providing innovative solutions that enhance efficiency and sustainability on a global scale [2]. Among these innovations, machine learning algorithms, particularly deep learning, have played a pivotal role in revolutionizing numerous facets of agriculture [3]. One of the most impactful developments in this field is precision agriculture, which represents a new era of modern farming. This evolution has been made possible by advancements in various technologies aimed at increasing yields sustainably and optimizing farm management [4]. Precision agriculture encompasses a wide range of techniques designed to improve accuracy and control in agricultural practices. These include GPS-guided tractors, robotics, remote sensing, and data analytics [5]. In precision agriculture, one of the most important aspects is fruit classification, which plays a crucial role in quality assessment. Among the fruits receiving notable attention in the Sahara region is the date, a nutritious fruit rich in carbohydrates, minerals, and vitamins known for its health benefits, including protection against illnesses like cancer and heart disease.

Globally, the production of date fruits is substantial, with an estimated yearly yield of 8.46 million tons [6]. According to the food and agriculture organization (FAO), Egypt, Saudi Arabia, Iran, and Algeria are among the top producers, with millions of tons produced annually [7] as detailed in Figure 1.

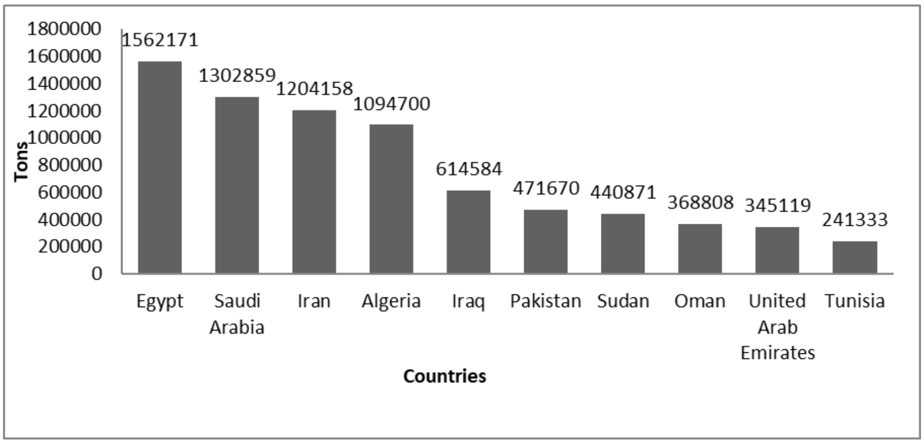


Figure 1. Top date producers in the world [7]

Given the importance of dates as staple foods in many regions, their classification and management are essential for optimizing production processes. Producers often face challenges in sorting and identifying various varieties and maturity stages of dates, tasks that can be efficiently addressed through AI and machine learning techniques [8]. The implementation of these technologies in agriculture has become the center of attention, providing precise solutions to improve date fruit management and processing [9].

In recent years, many studies have been published on the classification of date fruits using machine learning and deep learning techniques. Rybacki *et al.* [10] presented DateNET, a convolutional neural network (CNN) model specifically developed for the automatic classification of various date fruit varieties. The model achieved a classification accuracy of 93.41%, highlighting the potential of CNNs in this field. Similar to the work of [11], this study extended the use of CNNs for features extraction, focusing on color, shape, and size, and achieved an improved accuracy rate of 97.2%, the study used a smaller dataset of 500 images, focusing on three types of dates. Altaheri *et al.* [12] proposed a machine vision framework designed to classify date fruits based on type, maturity, and harvest readiness in a natural orchard environment. The framework uses deep CNN and transfer learning to achieve high classification accuracy with a rich dataset of over, 8,000 images. For type classification, the framework achieved an accuracy of 99.01% with times of 20.6 msec. Özaltin [6], tested algorithms such as decision tree (DT), K-nearest neighbors (KNN), and support vector machines (SVM) to classify seven date varieties. Although the neural network model achieved the highest accuracy (93.85%), these models offer a less computationally intensive alternative to deep learning approaches. Aiadi *et al.* [13] suggested hybrid models combining supervised and unsupervised learning methods as shown in integrated features from VGG-F (for supervised learning) and PCANet (for unsupervised learning) using the discriminant correlation analysis (DCA) algorithm for feature fusion. This method improved classification accuracy while reducing computational complexity. The study, using a large dataset of 20 date varieties, outperformed other deep learning-based methods. Alsirhani *et al.* [14] proposed deep transfer learning techniques for classifying 27 date varieties. Using a custom dataset of 3228 images, the researchers fine-tuned a DenseNet201 model, achieving a validation accuracy of 97.21% and a test accuracy of 95.21%.

Another important application of deep learning in date farming is the intelligent harvesting decision system (IHDS), proposed by Faisal *et al.* [15] it used computer vision and deep learning methods, including CNN architectures like VGG-19, Inception-v3, and NASNet, to figure out the best time to harvest based on seven stages of maturity. Achieved 99.4% accuracy, in addition to maturity and variety classification, surface quality assessment has also benefited from deep learning. Almomen *et al.* [16], the authors proposed a system aimed at enhancing the efficiency and accuracy of post-harvest processes by classifying dates into two primary categories: excellent and poor surface quality. To achieve this, they developed a new image dataset and employed various deep learning models, including YOLOv5n, YOLOv5s, EfficientNetB0, and EfficientNetB1. The performance evaluation demonstrated that conventional neural network models were effective in classifying the dates, with the EfficientNetB1 model achieving the highest accuracy of 97%.

Machine learning and image processing techniques have also been applied for variety classification. Koklu *et al.* [17], seven varieties of date fruits were classified using 898 images and 34 features, including morphological and color characteristics. The study applied machine learning methods like LR, artificial neural networks (ANN), and a stacking model, with the latter achieving the highest accuracy of 92.8%.

Several studies have explored modifications of existing deep learning architectures for improved performance. For instance, Albarrak *et al.* [18] modified the MobileNetV2 architecture with additional custom layers to classify eight common date varieties in Saudi Arabia, achieving a 99% accuracy rate. This study demonstrates the potential of the model in agricultural applications. Haidar *et al.* [19], utilized KNN, linear discriminant analysis (LDA), and ANN to classify and identify seven different varieties of date fruit. Among these techniques, ANN demonstrated the highest performance, achieving an accuracy of 99%.

In this context, our objective is to improve prediction accuracy and for this purpose we have opted for the following proposed approach to classify date fruits by selecting the two best-performing pre-trained models from the six deep learning models (InceptionV3, DenseNet121, MobileNetV1, VGG16, VGG19, and InceptionResNetV2) and concatenating their feature maps. After that we use three classifiers: SVM, ANN, and LR. Afterwards, we apply a stacking ensemble method, which combines these classifiers.

The remainder of this paper is structured as follows: After the introduction, we describe the proposed method and the specific approaches used in this research. The next section presents the experimental results, followed by a discussion of the findings. Finally, the conclusion is drawn in the last section.

## 2. MATERIAL AND METHODS

### 2.1. Dataset

The dataset used in our study was obtained from research conducted by Aiadi *et al.* [13]. This dataset consists of 1,619 images representing twenty different Algerian date varieties. These varieties include Ajina, Adam Deglet Nour, Bayd Hmam, Bouaarous, Deglet, Deglet Kahla, Deglet Ghabia, Degla Bayda, Dfar Lgat, Dgoul, Ghars, Litima, Loullou, Hamraya, Tarmount, Tanslit, Tantbucht, Techbeh Tati, Tivisyaouin, and Tinisin. Date samples were collected from local markets in the Touggourt region, which is situated in southern Algeria. The details of the dataset are provided in Table 1, which includes the number of samples for each variety. Figure 2 illustrates the displayed date varieties, and Table 1 illustrates the number of samples for each date fruit variety.


Figure 2. Sample images of twenty different types of date fruit

Table 1. Number of samples for each date fruit variety

| Date fruit type | Number of simples |
|---|---|
| Adam Deglet Nour | 86 |
| Ajina | 85 |
| Bayd Hmam | 87 |
| Bouaarous | 82 |
| Degla bayda | 95 |
| Deglet kahla | 85 |
| Deglet gharbia | 35 |
| Dfar lgat | 86 |
| Dgoul | 103 |
| Deglet | 38 |
| Ghars | 88 |
| Hamraya | 76 |
| Loullou | 81 |
| Litima | 85 |
| Tantbucht | 76 |
| Tarmount | 83 |
| Tanslit | 85 |
| Techbeh tati | 88 |
| Tivisyaouin | 87 |
| Tinisin | 88 |

## 2.2. Pre-trained CNN models

### 2.2.1. VGG16

VGG-16, also known as VGG-D, is a top-performing VGGNet model with 92.7% accuracy in ImageNet ILSVRC2014. It consists of 16 trainable layers, including 13 convolutional and 3 fully connected layers. The model uses 3×3 convolutional filters and 2×2 max-pooling layers, reducing spatial dimensions from 224×224 to 7×7. The number of filters doubles after each max-pooling layer, ranging from 64 to 512. rectified linear unit (ReLU) activation is applied after each layer, without normalization layers [12].

### 2.2.2. MobileNetV1

MobileNetV1 is designed for mobile and embedded vision applications, its primary innovation is the use of depthwise separable convolutions, which replace standard convolutional layers that are computationally intensive. This approach significantly decreases the number of parameters in the network, making it more efficient. Depthwise separable convolution consists of two stages: depthwise convolution, which processes each channel independently, and pointwise convolution, which combines outputs using 1×1 filters. The architecture is optimized for low-resource devices, enabling real-time processing while balancing performance and efficiency, making it ideal for computer vision tasks [20].

## 2.3. Classification methods

The classification process involved the application of the three following models:

### 2.3.1. Logistic regression

LR is a commonly used statistical method for modeling the probability of a binary outcome based on one or more explanatory variables. Its primary goal is to estimate the coefficients of a linear model that relates the logarithm of the odds (log-odds) to the independent variables. The mathematical formulation of LR is expressed as follows:

$$\log\left(\frac{P(Y=1\,|X)}{1-P(Y=1\,|X)}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n \tag{1}$$

where:
Y= (0 or 1) is the binary variable,
X= ($X_1$…,$X_n$) are the ‘n’ explanatory variables,
β = ($\beta_0$,…,$\beta_n$) are the regression coefficients to be estimated based on the data.

LR is widely applied across various fields, including physical sciences, social sciences, engineering, biomedicine, and agriculture. It is particularly effective for analyzing datasets with one or more independent variables that influence a binary outcome. The main advantages of LR include its simplicity of interpretation and its effectiveness in addressing binary classification problems. However, it is essential to avoid overfitting by selecting a parsimonious model with an appropriate number of explanatory variables [17].

#### 2.3.2. Artificial neural network

Neural networks are supervised machine learning models used for classification tasks. They mimic the human brain's structure with an input layer, hidden layers, and an output layer, where neurons process data. The network learns by minimizing errors through iterative adjustments. The hidden layers are critical for learning complex patterns, while the input and output layers handle data entry and results, respectively. To enhance performance, it's important to optimize the number of hidden layers and neurons, and apply techniques for error reduction and data normalization. Parameter tuning should align with the model's objectives for optimal learning outcomes [21]. In our ANN model, we utilized the ReLU activation function and employed the ADAM optimizer for effective training. The model is trained for 300 epochs, with these settings selected to optimize classification performance.

#### 2.3.3. Support vector machine

SVM is a supervised machine learning algorithm. It can be used for both classification and regression problems, but it is most commonly applied to classification tasks [22]. It works by transforming data characteristics into higher dimensions to establish a boundary or hyperplane for classification. The SVM identifies a linear discriminant function that maximizes the margin between different classes of data. Support vectors, which are data points closest to the classification boundary, play a crucial role in defining this boundary. SVM is well-known for its accuracy and versatility, making it a popular choice in applications like image recognition, object detection, voice analysis, fingerprint identification, and handwriting recognition [23].

#### 2.3.4. Stacking

Stacking is an ensemble machine learning technique that involves training multiple models to address the same problem and then combining their predictions to enhance overall performance. The primary goal of stacking is to create more accurate and robust models by effectively integrating the outputs of various weaker models. This approach has been shown to improve classification performance by aggregating the predictions of different classifiers into a single, more reliable estimation [17]. The stacking method used in the study is shown in Figure 3.

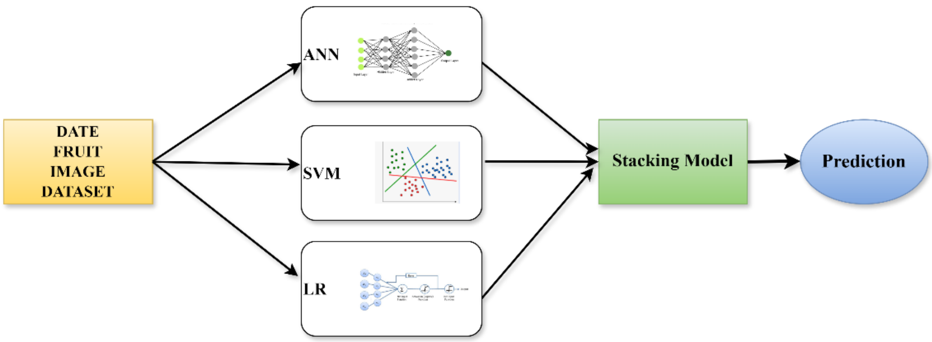


Figure 3. The created stacking model

## 3. EXPERIMENTAL SETUP

In our experiment, we have two stages presented as follows:

### 3.1. Stage 1: select the best models

In our experiment, we evaluate six popular pre-trained deep learning models: VGG16, VGG19 MobileNetV1, InceptionV3, DenseNet121, and InceptionResNetV2. It is important to identify which model will perform better. To choose the best deep learning model, we do the following experiments.

The dataset was divided into 80% for training and 20% for testing. The experiments were configured with 20 epochs and a batch size of 32, enabling a thorough evaluation of each model performance. The accuracy metrics obtained for these architectures are summarized in Table 2**.**

The training performance of different methods is shown in Figure 4. InceptionV3 Figure 4(a), DenseNet121 Figure 4(b), MobileNetV1 Figure 4(c), VGG16 Figure 4(d), VGG19 Figure 4(e), and InceptionResNetV2 Figure 4(f). MobileNetV1 and VGG16 attained the best accuracy rates of 95.37% Figure4(c) and 91.24% Figure4(d), respectively, among the six evaluated CNN architectures, whereas

InceptionResNetV2 had the lowest accuracy at 85.22% Figure4(f). The suggested hybrid approach utilizes feature maps obtained from these two best models.

Table 2. Accuracy values from CNN architectures

| DenseNet121 | VGG16 | MobileNETV1 | VGG19 | InceptionV3 | InceptionResNetV2 |
|---|---|---|---|---|---|
| 88.89% | **91.24%** | **95.37%** | 86.16% | 89.20% | 85.22% |

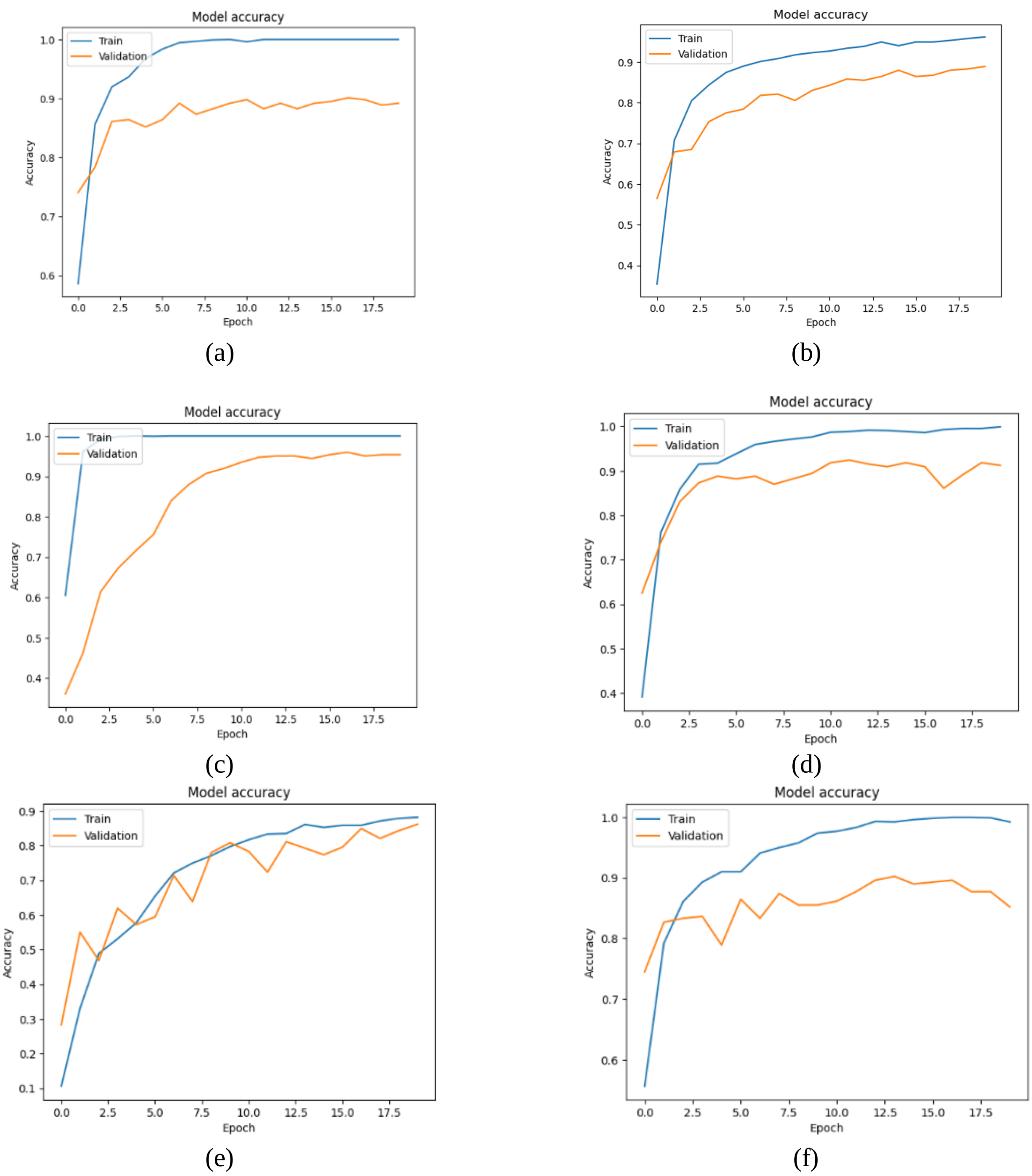


Figure 4. The training performance of different methods: (a) InceptionV3, (b) DenseNet121, (c) MobileNetV1, (d) VGG16, (e) VGG19, and (f) InceptionResNetV2

After selecting the models to use in our experiments, we implement a stacking ensemble approach (combining the three classifiers, SVM, LR, and ANN) to compare the results with each individual classifier. The results indicate that the stacking ensemble outperformed the individual classifier. The detailed results of these comparisons are presented in Table 3.

Table 3. The accuracy results obtained with different machine learning methods

| | SVM | ANN | LR | Stacking |
|---|---|---|---|---|
| VGG16 | 94.75% | 93.83% | 94.75% | **96.60%** |
| MobileNetV1 | 97.22% | 95.68% | 95.06% | **97.83%** |

### 3.2. Stage2: proposed model

In our work, VGG16 generates feature map with dimensions of (1,619×512) and MobileNetV1 generates feature map with dimensions of (1,619×1,024). After concatenation, the resulting feature maps have dimensions of (1,619×1,536).

In the next step, we employed three distinct classification algorithms (SVM, ANN, and LR) to the new feature maps. Each classifier was evaluated individually to assess its performance on the classification task. In addition, the stacking model created by combining these three algorithms was compared with the individual performance of each model. The general architecture is shown in Figure 5.

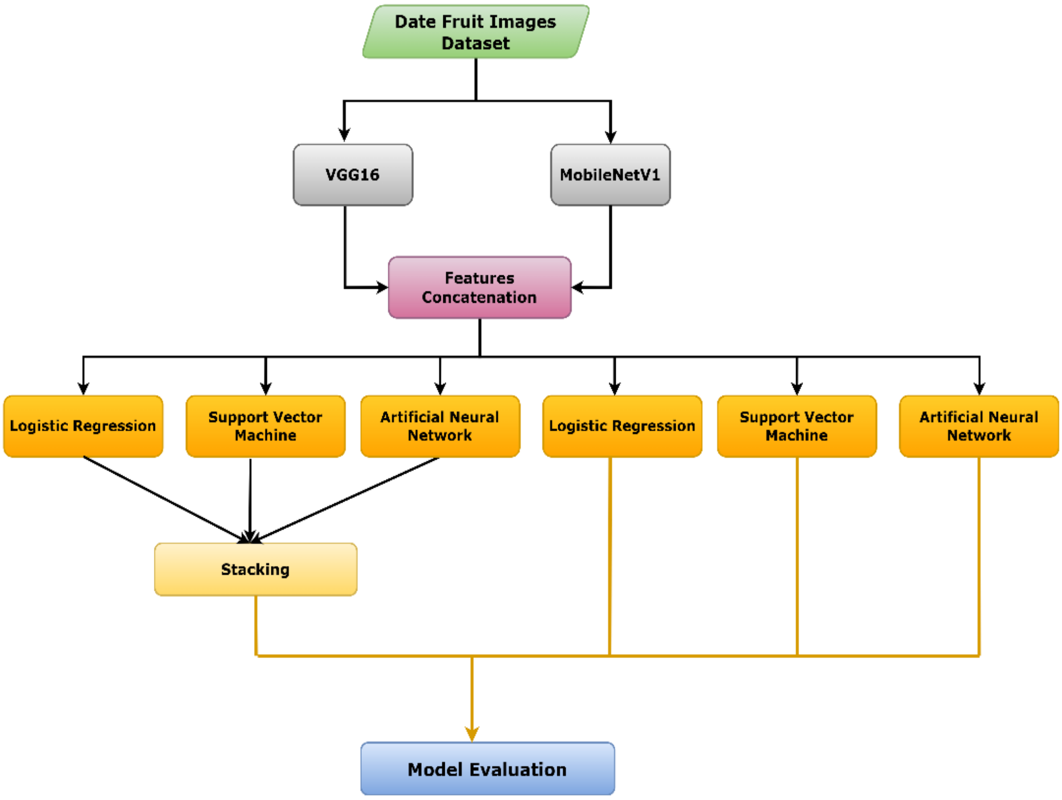


Figure 5. Architectural design of the proposed hybrid model

## 4. EXPERIMENTAL RESULTS AND DISCUSSIONS

### 4.1. Evaluation metrics used

In our study, we used several evaluations. These measures aim to evaluate the performance rate of our hybrid model. Precision, recall, F1-score, AUC, and accuracy were determined by quantifying the predicted classes based on the following quantities: the number of false negatives (FN), false positives (FP), true negatives (TN), and true positives (TP). The mathematical representation's definition is outlined below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

$$F1-score = 2 \times \frac{recall \times precision}{recall + precision} \quad (5)$$

AUC: the AUC value ranges from 0 to 1. As this value nears 1, the predictive value escalates, whereas as it nears 0, the predictive value diminishes [21].

### 4.2. Results

The results of our evaluation hybrid method are presented in Table 4, which presents essential metrics for evaluating the ANN, SVM, LR, and stacking model. The stacking model achieved an accuracy of 99.38%; this demonstrates the effectiveness and robustness of our approach. Figure 6 illustrates the confusion matrices for the respective classifiers, where Figure 6(a) represents SVM, Figure 6(b) shows LR, Figure 6(c) corresponds to ANN, and in Figure 6(d) the stacking model. In the stacking confusion matrix Figure 6(d), it evidently appears that most test samples were correctly classified.

Table 4. Performance results of classification performances

| Hybrid model | AUC | F1-score | Precision | Recall | Accuracy (%) |
|---|---|---|---|---|---|
| ANN | 0.9996 | 0.9722 | 0.9765 | 0.9722 | 97.22 |
| SVM | 0.9990 | 0.9849 | 0.9865 | 0.9846 | 98.46 |
| LR | 0.9997 | 0.9910 | 0.9926 | 0.9907 | 99.07 |
| Stacking | 0.9999 | 0.9938 | 0.9939 | 0.9938 | **99.38** |

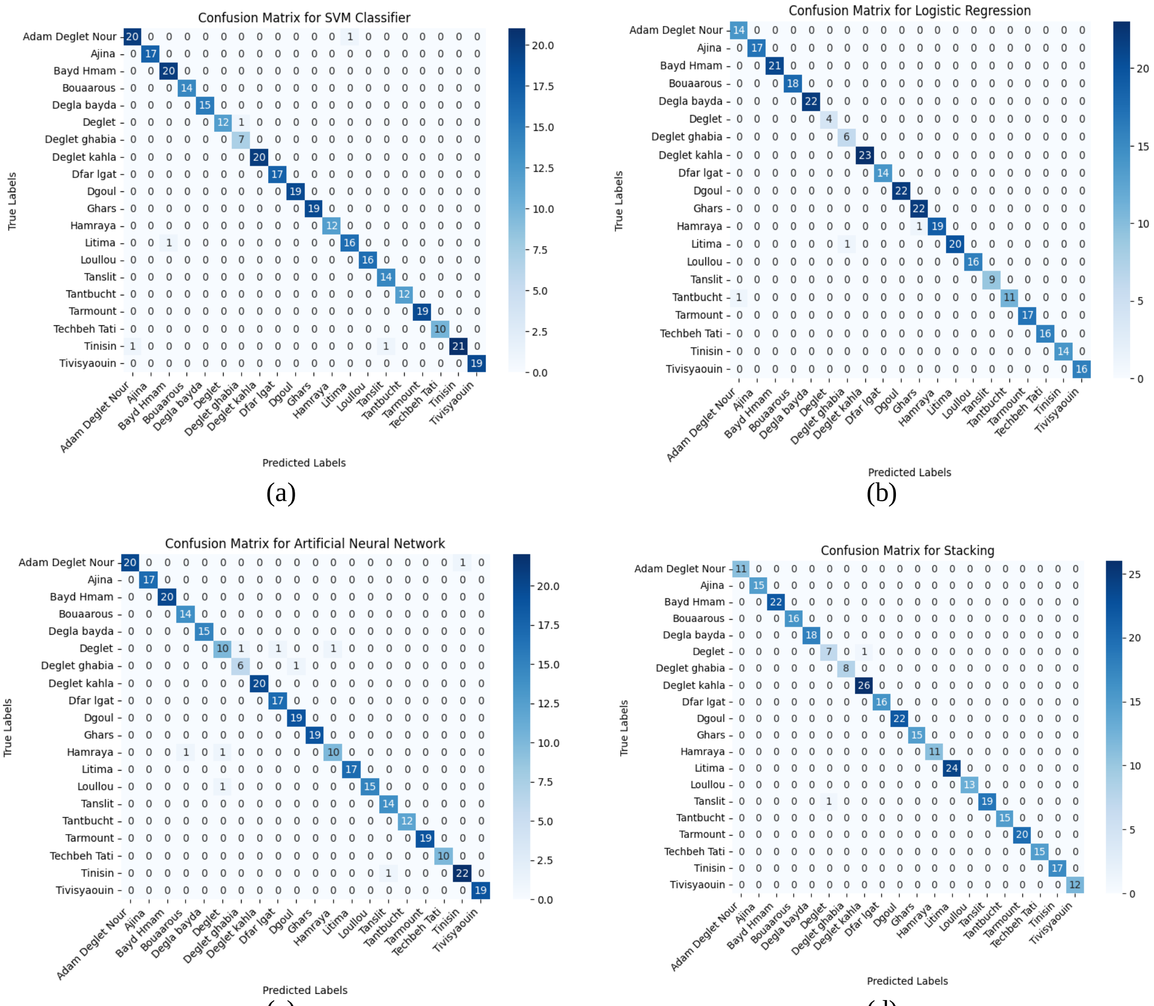


Figure 6. Confusion matrices of classification algorithms: (a) SVM, (b) LR, (c) ANN, and (d) stacking

Our proposed model is evaluated against several recent state-of-the-art techniques, as presented in Table 5. Our hybrid model demonstrates superior performance using a dataset with 20 different types of date fruit, which makes the learning process more challenging compared to models trained on datasets with fewer classes. With more classes, the model must differentiate between a larger number of categories, increasing the complexity and difficulty of the training process. In Table 6, we analyze the performance of our hybrid method against another approach tested on the same dataset [11].

Table 5. Comparison with state-of-the-art methods

| Ref | Years | Technique | Date types | Accuracy |
|---|---|---|---|---|
| [17] | 2021 | Stacking model created by combining LR and ANN | 7 | 92.80% |
| [11] | 2019 | Features extraction+ combination of several hidden layers | 3 | 97.20% |
| [24] | 2021 | MobileNetV1 | 6 | 82.67% |
| [25] | 2020 | Resnet50 | 5 | 97.37% |
| [26] | 2022 | AlexNet | 9 | 94.20% |
| [27] | 2019 | VGG16 | 4 | 96.98% |
| [28] | 2021 | VGG19 | 1 | 99.32% |
| | Proposed model | Features extraction using VGG16 and MobileNetV1+stacking (SVM, LR, ANN) | 20 | **99.38%** |

Table 6. Comparison of works with proposed approach using the same dataset

| Writer | Technique | Accuracy |
|---|---|---|
| [13] | VGG-F+PCANet+CCA | 99.32% |
| Proposed model | Features extraction using VGG16 and MobileNetV1 + stacking (SVM, LR, ANN) | **99.38%** |

## 5. CONCLUSION

The principal objective of our study is to get high accuracy in classifying various varieties of date fruits and the findings validate the efficacy of our model. To achieve this goal, we proceeded with a hybrid classification method for date fruit that achieved the best accuracy of 99.38% after applying two stages of experiments. In the first stage, we choose the two best-performing pre-trained models from six deep learning models, and we concatenate the feature maps extracted from these two models. In the second stage, classification is performed using machine learning models such as ANN, SVM, and LR, after that we applied a stacking model that combines these three classifiers. Our proposed method has outperformed several state-of-the-art methods, furthermore; the model might be made more accessible and useful for the agriculture sector or made available via mobile devices. In the future work will apply this hybrid model to other agricultural products, aiming to enhance classification accuracy and operational efficiency across various agricultural contexts.

## AUTHOR CONTRIBUTIONS STATEMENT

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

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

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author O, Aiadi [13] on request.

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