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Innovative Date Fruit Classifier Based on Scatter Wavelet and Stacking Ensemble

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Abstract

Dates are essential fruits loaded with vital nutrients that keep bones healthy and prevent bone-related disorders. Approximately 8.46 million tons of different types of dates are cultivated and produced annually around the globe. There are more than 400 types of dates that are time-consuming and expensive to produce. Classifying them using conventional methods is labor-intensive, and this is one of the biggest problems for the date industry. Dataset fruit classification plays a vital role in the food industry. Dates can be classified from a luxury class to a less quality class. Accordingly, the food industry needs an automotive date fruit classifier that can work in food factories. This study proposes a pioneering method to classify date fruit that relies on extracting features from the texture of dates using Scattering Wavelet Transformation (SWT). The SWT yields in numeric coefficients were found to be immune to the deformation of invariants. This feature set trains an ensemble classifier that combines a voting mechanism to eliminate overfitting. The ensemble classifier consists of a random forest, a support vector machine classifier, and a logistic regression hyper-learner. Our novel approach was tested on two benchmarked datasets. The first data set scored F1 between 0.95 and 1.0 at the same time. The second dataset registered F1 between 0.96 and 1.0 in each of the 20 date classes. Some dates are close to each other in texture, resulting in high false positives or recall, causing a lower F1 score accuracy degree. The novelty of this approach comes from the featured representative of each date class, relying on the texture of the fruit as a discriminative feature, not on the fruit shape or color, which may not be robust enough as distinguishable features, especially in date classes that are close to each other in shape.

Keywords: Dates; Scatter Wavelet Transform; Stacking Ensemble Learning; Random Forest Classifier; Linear Support Vector Machine; Performance Metrics.

1. Introduction

Food is one of the essential requirements for the human body's development, restoration, and tissue preservation, which regulate fundamental processes. To meet the basic need for the sustenance and survival of the world's rapidly growing population, the agricultural sector works day and night. Agriculture plays a crucial role in the economic growth of nations, prompting industries to continuously seek enhancements in all aspects of agricultural operations by employing artificial intelligence (AI) technologies, smart agriculture, and precision agriculture [1].

Fruits such as dates represent an important component of the human diet due to their nutritional value, providing a great source of calcium, iron, potassium, and vitamin C [2]. Dates have been commonly cultivated in the Arabian region since 6000 BCE, and approximately more than 8 million tons are produced annually all over the world [3]. In 2019,

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statistics showed that Asia and Africa were the most dominant zones, producing 57% and 42.2% of dates, respectively [4]. There are more than 400 different types of dates, and over 40 of these are unique, with a wide variety of tastes, shapes, and colors, as well as values and prices. Because many consumers struggle to distinguish between the various types of dates, the process of classifying and identifying dates is crucial and represents a pivotal importance to food, agriculture, medicine, and trade [5–7]. The conventional methods used to classify dates are time-consuming, tedious, and expensive [8]. The development of image classification through AI systems has good durability at a low cost, as well as offering high precision and being computationally fast to evaluate fruits in adverse weather and typical environmental conditions [9]. As a result, industries have adopted computer vision techniques to classify grades and sort dates depending on several features such as color [7–10], texture [7], and size [11], which were previously managed manually [1].

Altaheri et al. [12] proposed a framework for date fruit classification by utilizing transfer learning with fine-tuning based on pre-trained Convolutional Neural Network (CNN) models. They compared their work with previous methods that utilized color distribution with Support Vector Machine (SVM), and the proposed model achieved high accuracy between 0.97 and 0.99. This study added some complexities that led to a decrease in accuracy, like variation in maturity levels, scale, angle, illumination, and bagging state.

Shikawa et al. [13] worked on another type of fruit, strawberries. They proposed a model that classifies strawberries based on shape features like measure values, ellipse similarity, chain code subtraction, and elliptic Fourier descriptors. In this study, various combinations of the mentioned deception features were tested. The best feature set was the use of measured value chain code subtraction with ellipse Fourier descriptors, which had high accuracy. However, the model faced a weakness in classifying nine types of strawberry shapes.

Rybacki et al. [14] designed an architecture for a convolutional neural network for classifying date palm fruits based on geometric and color features. Their proposed CNN model outperformed previous models like ResNet, ShuffleNet, and MobileNet. The model extracted geometric features for date fruits such as major diameter, perimeter, and length, helping improve model accuracy.

Albarrak et al. [1] proposed a model for date fruit based on MobileNetV2. The dataset was prepared and photographed using a 12-megapixel camera to ensure good-quality date images. They collected between 204 to 2040 images for each of the eight date fruit classes. The model was fine-tuned by the dropout mechanism to avoid overfitting. Despite the model's training accuracy achieving 0.99 accuracy, the model faced challenges in the test set and scored about 0.64 accuracy. This led to real concern about overfitting due to the low accuracy in the validation set, which resulted in the model’s results not being generalized.

The previous papers tried to design a classification paradigm based on shape, color, and other geometric features by using either machine learning or deep learning models. Although previous researchers achieved good performance, their works refer to the fact that color and shape cannot always be reliable discriminative features for date classification for the following reasons: First, some date classes have the same shape or color ranges, making it difficult to identify between them based on just these features. Second, the similarity of ripeness in fruit. For example, the unripe dates may have the same green or yellow hue, while the ripe dates may look blocked in most of the date fruit classes. So, the classifiers cannot work robustly just on color. Last, physical damage can be caused during fruit growth, leading to misshapen fruit. From all previous studies, this paper tried to design a date fruit classification that can go beyond the current success rates by using the texture feature of each date fruit class. Accordingly, we designed a system to convert texture features into numeric coefficients using the scattering wavelet transform as a discriminative feature for each date class. The major contributions are illustrated in the following points:

- The use of the scattering wavelet for feature extraction allows the building of an accurate classifier that can be trained with a small dataset, especially if there are not enough samples for the class.
- Building a classifier that can work with reasonable accuracy without over-fitting, and this can be achieved by using an ensemble machine learning classifier, as this paradigm is based on voting that prevents over-fitting.

This model is based on building a classifier based on the texture magnitude of the scattering wavelet rather than depending on the shape or color of the date fruit, which may be common in many classes, causing inaccuracy in the model. The remainder of the paper is arranged as follows: In Section 2, related works are presented. Scatter wavelet transform and stacking ensemble learning are explained in Sections 3 and 4, respectively. Section 5 illustrates the evaluation metrics. The methodology and proposed model are explained in Section 6. The results and discussion are provided in Section 7. Finally, Section 8 draws some conclusions and future work recommendations.

2. Related Works

According to previous studies, computer vision techniques have been adopted to automatically process date fruit classification based on machine learning and deep learning techniques. Fadel (2007) [15] discussed the classification of varieties of date fruit from the RGB channels based on mean and variance. Subsequently, they utilized a Probabilistic Neural Network (PNN) to train and test the samples. Back propagation and Radial Basis Function (RBF) networks, coupled with the method of Multilayer Perceptron (MLP), were used to classify the features extracted from images of date fruit, achieving success rates of up to 87.5% and 91.1%, respectively [16]. Muhammad (2014) [6] initially separated each image used into its color constituents. Then, each component underwent Weber Law descriptor (WLD) and Local Binary Patterns (LBP) applications to determine the texture of the dates. SVM has been used as a classifier and has gained 98% accuracy. This approach is advantageous as the texture of date fruits can vary depending on their maturity level, making the use of texture descriptors quite practical.

The convergence of artificial intelligence was efficient in classifying date fruit; these techniques of boosting, bagging, support vector machine, k-nearest neighbor, and MLPs recording accuracy between 90-92%, the codes available on Github [17]. Previous studies also used machine learning approaches to identify seven classes of date fruit. In past experiments, hyper-parameters were fine-tuned for each K-Nearest Neighbor (KNN), Artificial Neural Networks (ANN), and SVM to classify date fruit. The dataset was divided into 80% training and 20% testing sets. The training set was divided into five for the validation process to check for overfitting. This study scored an accuracy rate of 93.85% [18]. A novel Hue, Color-SIFT, Discrete Wavelet Transform, and Haralick consolidation method exceeded other features used in fruit classification problems. Various features like color, shape, and texture were used to compare the results yielded by six machine learning algorithms, including KNN, SVM, Naïve Bayes, Linear discriminant analysis, decision trees (DT), and Feedforward Neural Network (FNN). All the mentioned methods were tested on a 360-date fruit dataset. The best result was obtained by a back propagation neural network, then SVM, and then KNN classifiers in terms of the accuracy of mean scores [19]. Ammari et al. [11] studied the evaluation of Khalas, Khenaizi, Fardh, Qash, Naghal, and Maan dates using dedicated computer vision. The pre-processing and segmentation of date images were the first steps in the system. Then, shape, size, and color were extracted and used in the ANN to predict the suitable class of an input date image.

The accuracy of the model was assessed using a confusion matrix with 97.26% highest classification accuracy. Abi Sen et al. [20] showed a comparison of several automatic classification algorithms using six extracted features based on color, size, and texture. The dataset used in the study consisted of images of four primary types of dates. The SVM classifier achieved a better precision of 0.73 compared with other classifiers, and their accuracies ranged between 0.6 and 0.69. They suggested that accuracy could be improved by gathering more data since the dataset used in the experiment was limited to just a few hundred images. Koklu et al. [21] utilized some features to build a system that distinguished between various species of date palm fruits. These features were shape, color, and morphology retrieved from the image dataset and tested with distinct machine learning models like neural networks and logistic regression to reach an efficient classifier. The performance of these methods achieved 91.0% and 92.2%, respectively. In another study, five date varieties were classified with an accuracy of up to 98% using the Sequential Minimal Optimization (SMO) and Instance-based learning algorithms (IBk) approaches. The date varieties were converted into individual color channels, and their texture parameters were extracted. To achieve better accuracy, a feature selection algorithm was applied, and those selected features were used as inputs into machine learning models (Bayes, Lazy, Meta, and Trees) for discriminating different varieties of date palm fruit [22].

Deep learning has been used to classify dates. Magsi et al. [23] introduced a methodology for recognizing date fruits. The methodology used deep CNN to extract features from a dataset of 500 images, which contained three types of Pakistan's date fruits. The classification model achieved 97.2% accuracy. To enhance the accuracy and efficiency of date classification after harvesting the crop, three subsets consisting of 55, 55, and 5 images were trained with YOLOv5n, YOLOv5s, EfficientNetB0, and EfficientNetB1. The evaluation results show the efficiency of the model in classifying the quality of date fruits based on convolutional neural network CNN models. EfficientNetB1 models were the best, with an accuracy of 97% on a date fruit image dataset [24]. Khayer et al. [5] evaluated pre-trained CNNs such as MobileNet and InceptionNet to classify six different types of dates, namely Ajwa, Boroy, Medjool, Moriam, Sokire, and Sugaey. The MobileNet_V1 model achieved 82.67% accuracy performance. The utilization of CNN is examined in Alhamdan & Howe [25] for categorizing images of date fruits into nine different types. Multiple models were developed, and the most successful model achieved an accuracy of 97%. Another experiment was carried out to compare CNN for five different kinds of dates, and ResNet-50 was found to perform better than the other networks with an accuracy of 97.37%, as stated in Al-Sabaawi et al. [26]. Alresheedi et al. [27] evaluated the detection performance and accuracy of many traditional ML techniques and CNN. The results of nine types of dates show that Multi-Layer Perceptron (MLP) had the best detection accuracy, whereas CNN achieved the maximum precision with 94.2%.

Alsirhani et al. [7] compiled a dataset consisting of 27 categories and 3228 images using five stages. In the first stage, they measured feature accuracy using pixel intensity and color distribution with conventional machine learning algorithms. They used traditional machine learning methods to evaluate the precision of characteristics, relying on color distribution and the intensity of the pixels. Next, they specified the model with the highest accuracy by utilizing deep transfer learning (TL). The third-step feature extraction part of the model was based on numerous re-trained points to determine the ideal point. In the fourth stage, they fine-tuned the hyperparameters for fully connected layers to specify the best configuration that would lead to accurate classification. In the fifth stage, the regulation of the classification layer to finalize the best model was selected from the fourth stage. The accuracy achieved was 95.21%. The date fruits dataset was augmented using an innovative Cycle Generative Adversal Network (CycleGAN) method and Deep Convolutional Generative Adversarial Networks (DCGAN). The augmentation process succeeded in increasing the dataset of the classes Suckari, Ajwa, and Suggai. At the same time, the researchers used the ResNet152V2 and CNN transfer models. The ResNet152V2 method performed well with an accuracy of 96.8%, while the CNN model accuracy registered about 94.3% [28]. Nadhif & Dwiasnati [29] tested CNN with a dataset of nine date fruit classes. The dataset was divided into 1496 images for training and 162 for testing. The accuracy indicates the efficiency of CNN models, with an accuracy of 96%. Other researchers used an intelligent harvesting decision system called IHDS to harvest data with six DL systems, each producing different accuracy levels. The dataset used was collected by the Center for Smart Robotics Research. The maximum accuracy registered by the IHDS system was 99.4% [30]. Table 1 shows the summary of related work.

3. Feature Extraction Scatter Wavelet Transform (SWT)

Texture is a crucial element for examining the surface of different types of images and classifying the objects. Each image has a distinct (unique) texture that can be used to compare with other images [31]. A SWT was constructed by Mallat [32]. A wavelet scattering network computes a representative in terms of a translation-invariant image where deformation does not influence the representative coefficients and maintains high frequency. It combines non-linear modulus and averaging operators with wavelet transform convolutions in a cascade. A scattering transform is based on its mechanism in the deep convolution network paradigm. There are two differences. First, the outputs of a scattering deep network are coefficients. Second, the scattering deep networks rely on pre-defined filters. Scattering networks do not use filters that are learned from data, but wavelets [33]. Figure 1 illustrates the effectiveness of scattering representation in discriminate textures that have the same power spectrum and second-order moments.

Table 1. Summary of related work

Study	Classification Technique	Date Varieties	Classifier	Accuracy
[20]	SVM	4 main types	SVM classifier	73%
[15]	Probabilistic Neural Network (PNN)	5 types of date fruit	PNN	The mean of 5 types (80%)
[5]	Pre-trained CNN models	6 types of date fruit	MobileNet, InceptionNet	82.67%
[16]	Back propagation and radial basis function (RBF) networks, coupled with the method of multilayer perceptron (MLP)	3 types of date fruit	MLP	87.5% 91.1%
[23]	Deep CNN	3 types of Pakistan's date fruit	CNN	89.2%
[21]	(ANN) and logistic regression (LR)	9 types of date fruit	ANN LR	91% 92.2%
[17]	Boosting, SVM, KNN and MLPs	6 types of date	Combined ML+AI	92%
[14]	Color based and geometric parameters	5 types of date	CNN	For both 93.4%
[18]	DT, SVM, KNN, ANN	7 types of date	ANN	93.85%
[27]	Traditional machine learning techniques and CNN	9 different types of date fruit	MLP, CNN	MLP (best detection performance), CNN (94.2% accuracy)
[28]	DCGAN	3 types of date (628) images	CNN	94.3%
[29]	CNN	9 types of date (1658) samples	CNN	96%
[24]	EfficientNet, Yolov5, andYolov5n	One type and 3 classes	CNN	97%
[25]	Convolutional Neural Networks (CNN)	9 different types of date fruit	CNN	97%
[7]	First stage using conventional machine learning algorithms, after that using a deep transfer learning (TL) model	Has 27 classes	TL	97.21%
[11]	ANN	6 types of date fruit	ANN-tansig classifier	97.26%
[26]	Pre-trained CNN models (ResNet-50)	5 types of date fruit	ResNet-50	97.37%
[2]	Support Vector Machine (SVM)	4 types of date fruit	SVM	98%
[22]	SVM	5 types of date fruit	SVM	98%
[34]	Fusing supervised and unsupervised deep networks	1619 images from 20 different date varieties	KNN classify	98.20%
[30]	6 different DL systems	7 stages of date	DL	99.4%

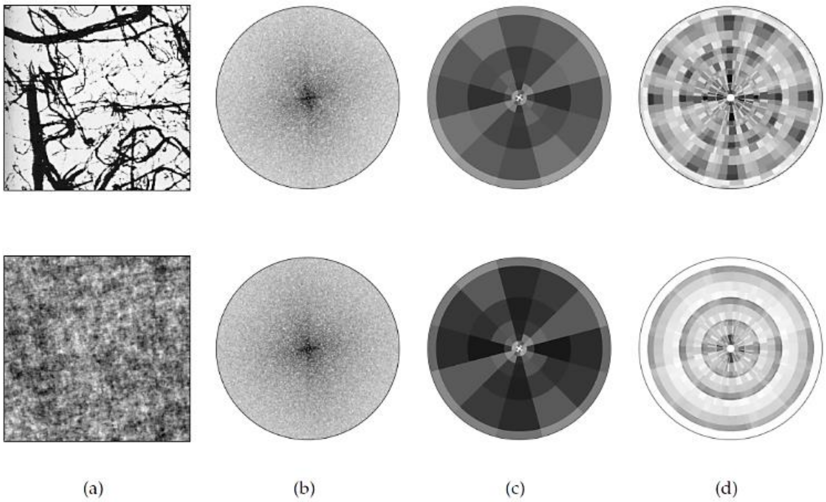


Figure 1. Two various texture samples have the same spectrum of Fourier [33]

Therefore, texture features extracted from SWT and scatter wavelet have some properties as follows:

- The SWT is stable and invariant to rotation, translation and color discrimination [35].
- It maintains class distinction and is stable under tiny deformations [33].
- Excellent in classification [33].
- When minor deformation and rotating invariance are combined, SWT coefficients are more descriptive than Fourier and can extract reliable information at a variety of scales [36].
- The SWT does not need a training process with the same functionality as CNN.
- A scattering transform is the linear series of wavelet transform and nonlinear modulus.

The network produces a representative Φ that is invariant to color operations of discrimination, rotation and translation [32]. Since the windowed scattering transform has a convolutional paradigm, each layer is acquired from the previous using wavelet value decomposition. U on individual envelope $[p]f$. The output layer is obtained by θj. Scattering is selected because it computes iteratively by employing U, inverting *Sj* needs inverting, so it can collect the coefficients repeatedly. Figure 2 illustrates the operation of a scattering wavelet network. If p is a path that has length of m, then the scattering coefficient $SJ\ [p]x(u)$ of order m at the scale $2J$. So, the scattering coefficient is computed at the CNN layer of m. First order coefficients $SJ\ [\lambda 1]x$ are equivalent to SIFT coefficients. The first order coefficients are not enough for text discrimination. Because of that, wavelet coefficient amplitudes $|x \star \psi\_| \star \varphi J\ (u)$ must be averaged.

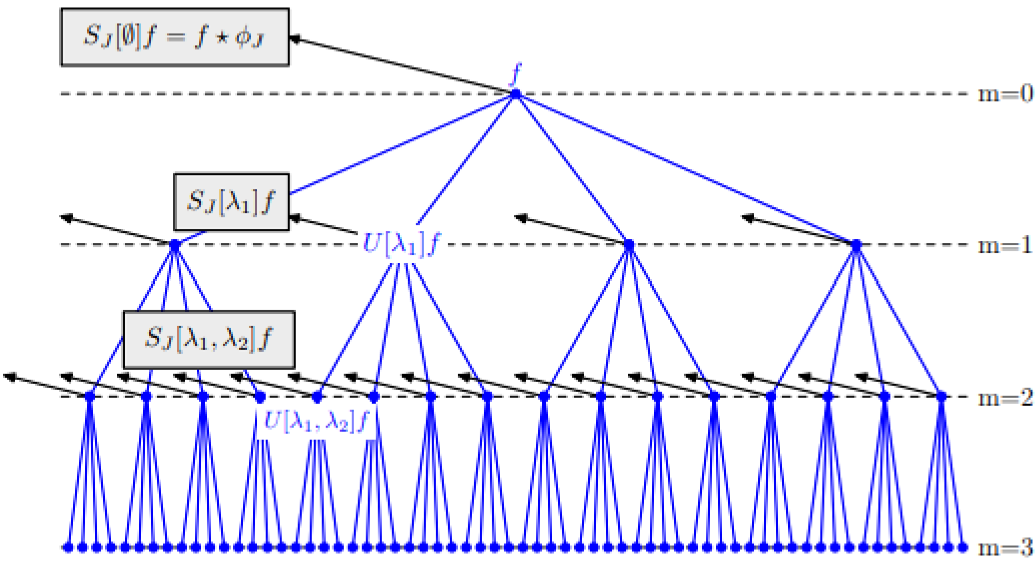


Figure 2. A spread of applying the operation of scattering wavelet network [33]

Equation 1 is a summary of the process of extracting scattering coefficients. The image is filtered using the first wavelet transform W_1. A complex wavelet has scaled and rotated for producing the modulus to characterize the first scattering layer $U_1\ y$. Therefore, the later layer calculates $U_2\ y$ by the modulus of W_2. Scattering coefficient S_3x develops from a final pooling. The pooling is known as average-pooling (AVG) or max-pooling specified by the blocks of size.

$$y \rightarrow |W_1| \rightarrow U_1\ y \rightarrow |W_2| \rightarrow\ U_2\ y\ \rightarrow\ \emptyset_J\ \rightarrow\ S_3\ y \tag{1}$$

The initial beginning wavelet layer is depicted by the base ψ1 (u) to determine higher order coefficients, and frequencies with lower values are filtered by $\varphi 2J\ (u)$. This wavelet signal is measured by $2j$ where j is an integer and rotated by $\theta 1\ = \frac{2k\pi}{K}$ for 0 _k < K that in Equation 2:

$$WJx(u) = \{x\ \star\ \varphi 2j\ (u), x\ \star\ \psi_u(u)\} \curlywedge \epsilon \Lambda j \tag{2}$$

where ψ_u is a Morlet wavelet, and φ Gaussian average filter.

$$\Lambda j = \{\curlywedge =\ 2^j \mathrm{r} :\ \mathrm{r}\ \in\ G^+, \mathrm{j}\ \geq\ -\mathrm{J}\}$$

This wavelet transform is obtained by filtering an image $x(u)$, wavelet modulus is then conducted on the wavelet value to keep the low frequency by averaging, and computes the modulus of complex wavelet coefficients in Equations 3 and 4:

$$U1x(u, w1) = |x\ \star\ \psi^1_{w1}(u)| \tag{3}$$

$$U1x(u, w1) = |\sum x(u)\psi^1_{w1}\ (u - v)| \tag{4}$$

Despite that, the averaging by $\varphi 2J$ minimizes the high frequencies but is used to aggregate coefficients to build an invariant. The loss is retrieved as wavelet coefficients that describe the significance of operating a multilayer network. The spatial variable u is sampled by $2j1 - 1$. The aggregated variable is computed by $u1 = (u, w1)$. The next layer is specified with a second wavelet in Equation 5 that is extracted by convoluted u1 coefficient by $u1x(u1)$ in another wavelet and spatial rotation, scale, variables $u1 = (u, \theta 1, j1)$.

$$\psi^2_{w_2}(u_1) = \psi^a_{j_2}(u)\ \psi^b_{k_2}(\theta_1)\psi^c_{l_2}(j_1) \tag{5}$$

Then save the scattering coefficients along paths of length $m \leq m\ max$ in the Equation 6.

$$SJ\ [p]x\ =\ U[p]x\ \star\ \varphi 2J \tag{6}$$

where $U[p]x$ is stating the scattering averaged for every layer in Equation 7 [33]:

$$UJ\ U[p]x\ = \{U[p]x\ \star\ \varphi 2J\ , |U[p]x\ \star\ \psi\ \curlywedge |\} \tag{7}$$

4. Stacking Ensemble Learning

The stacking Ensemble Learning procedure is based on linking the predictions of several machine learning models using a separate method. It represents a means of improving the accuracy of machine learning models. Stacking is particularly useful when there are several models that are good at different aspects of a given task. In this case, separate machine learning is trained to learn how to make the best use of predictions from the various models. The stacking technique involves two-level models: the constructing model, which is stated as the level-0 model, and the level-1 model, which is the meta-learning approach, which trains another model to combine the predictions from these essential models. The fundamental concept behind stacking is centered on the level-0 base classifiers being trained with the training data, and then the models are supplied with unseen data. Both the predicted target labels, which were produced on the unseen data, and the actual labels are combined into one dataset, which is used to train the meta-learner. Meta-learning is machine learning that trains algorithms using the output of other ML methods for accurate predictions. In our proposed model, the construction level-0 models are the Support Vector Machine (SVM) model and Random Forest (RF) model, which are given as input to the meta-level model or level-1 model, which is the Logistic Regression model (LR) [37]. Figure 3 shows the schematic view of the stacking ensemble learning model that is used in this research paper.

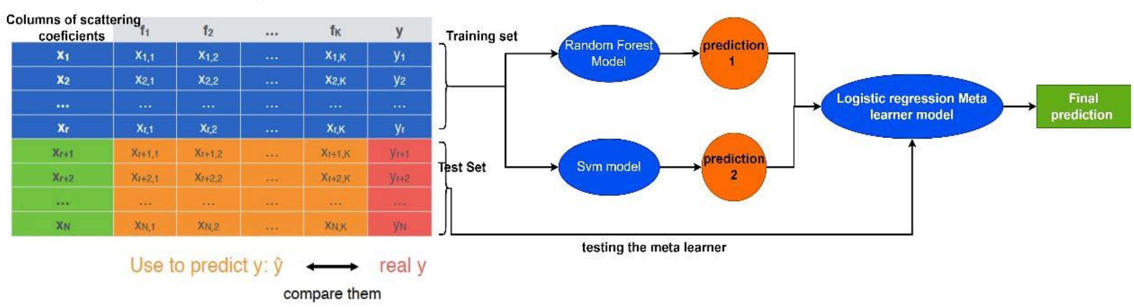


Figure 3. Topology of the stacking ensemble learning

5. Evaluation Metrics

By formulating dates as a classification problem, the proposed method defines the metrics to include accuracy, precision, recall, and F-measures that agree, evaluating the performance of a classifier from various perspectives. These metrics have been used and obtained from the 2 × 2 confusion matrix in Figure 4.

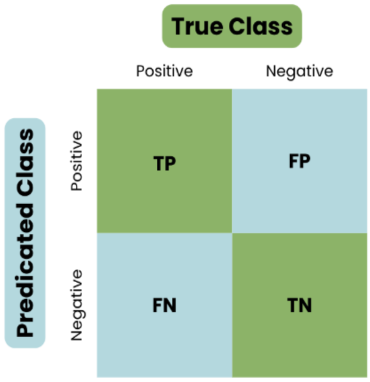


Figure 4. Confusion matrix

Generally, accuracy, precision, recall, and the F-1 score were used to obtain the performance measures from the confusion matrix. The confusion matrix for the model included four cases, which were used to derive more advanced metrics. These cases included:

- True Positive (TP): The real and the predicted values are identical (positive).
- False Negative (FN): The real value is positive.
- False Positive (FP): The actual value is negative.
- True Negative (TN): The actual and the predicted values are the same (negative).

These metrics are computed using the following expression [38]:

1) Precision:

Precision in Equation 8 is evaluated by dividing the total number of true positive samples with the total number of true positive and false positive samples.

$$\text{Precision} = TP/(TP+FP) \tag{8}$$

2) Recall:

A recall as in Equation 9 is computed by dividing the total number of true positive samples with the total number of true positive and false negative samples. The recall measure is employed to judge the model's capacity to detect positive samples. The higher recall shows more positive samples.

$$\text{Recall} = TP/(TP+FN) \tag{9}$$

3) Accuracy:

Accuracy indicates the percentage of correctly predicted data. Accuracy is computed by dividing the total number of true positive and true negative samples with the total number of true positive, true negative, false positive and false negative samples as in Equation 10.

$$\text{Accuracy} = ((TP+TN)/(TP+TN+FP+FN))\times 100 \tag{10}$$

4) F1-score:

The F1-score in Equation 11 Combines the precision and recall results in data classification that provide overall prediction performance.

$$\text{F1-score} = (2\times(\text{Precision}\times\text{Recall}))/(\text{Precision}+\text{Recall}) \tag{11}$$

The Receiver Operator Characteristics (ROC) Curve is also operated to determine the performance of the model. In the ROC curve, specificity is exposed on the x-axis and sensitivity is shown on the y-axis. The value of the area under the ROC curve (AUC) varies between 0 and 1. As this value is close to 1, the predictive value increases, and as it is close to 0, the predictive value decreases. In Figure 5, the ROC curve and AUC area are shown [39].

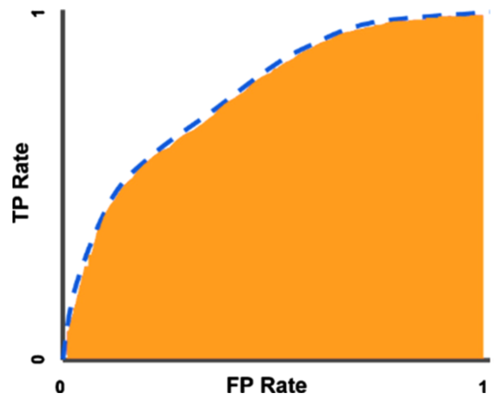


Figure 5. ROC curve (blue dotted line) and AUC area (Orange zone)

6. Research Methodology

6.1. Dates Fruit Dataset

Date fruit images were collected from Kaggle (Alhamdan) [40]. It contains nine classes of different common market date types named Ajwa, Galaxy, Medjool, Meneifi, Nabat Ali, Rutab, Shaishi, Sokeri and Sugaey. Each class has approximately 180 images, with 1658 total samples. Figure 6 shows the type of each class.

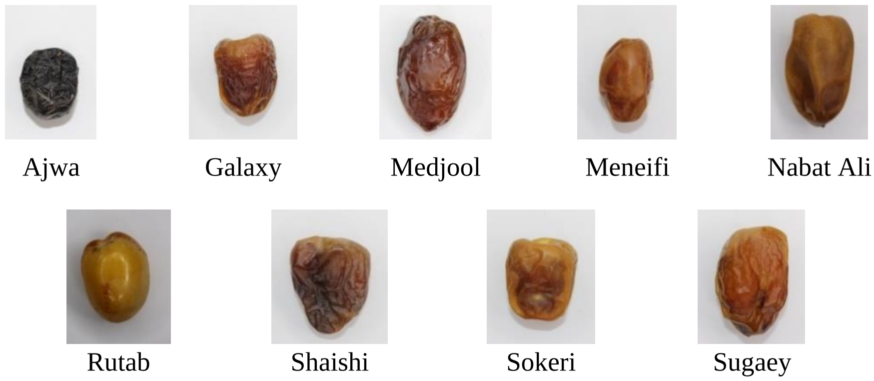


Figure 6. Sample of nine dataset

Figure 7. From left to right, displayed date varieties are 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.

The second dataset by Aiadi et al. consists of 20 classes (Ajina, Adam, Deglet Nour, Ghars, Litima, Bayd Hamam, Deglet Kahla, Bouaarous, Deglet Bayda, Tarmount, Tanslit, Deglet, Tantbucht Tati, Tivisyaouin, Tinisin, Loullou and Hamraya) as illustrated in Figure 7.

6.2. Image Pre-Processing

Image pre-processing is a fundamental phase of a computer vision technique. It encompasses preparing images prior to their usage in model training and inference. It can include tasks such as resizing, orienting, and correcting color. This process can possibly reduce model training time and maximize model inference. When dealing with large input images, decreasing their size can improve the training time of a model considerably without significantly compromising its performance. In this proposed method, images are converted to grayscale and resized to 200×200 for better accuracy.

6.3. Proposed Model

Figure 8 depicts the main steps of the proposed date classification model. The color images of dates are fed into the pre-processing step to convert them into a proper shape of 200×200 pixels of type gray images. Before building the classifier model, the feature extraction step should be conducted by implementing the scattering wavelet extraction process. After that, each date's features will be represented by a one-dimensional vector. Finally, the one-dimensional feature's vector will be inputted into the stacked ensemble learning model.

The proposed model was implemented with an i7 processor and 32 GB of RAM. Google Colab was used for running the software settings, which involved Python version 3.8. The machine learning libraries employed during the experiments included Pandas, NumPy, Sklearn pre-processing, and Sklearn metrics.

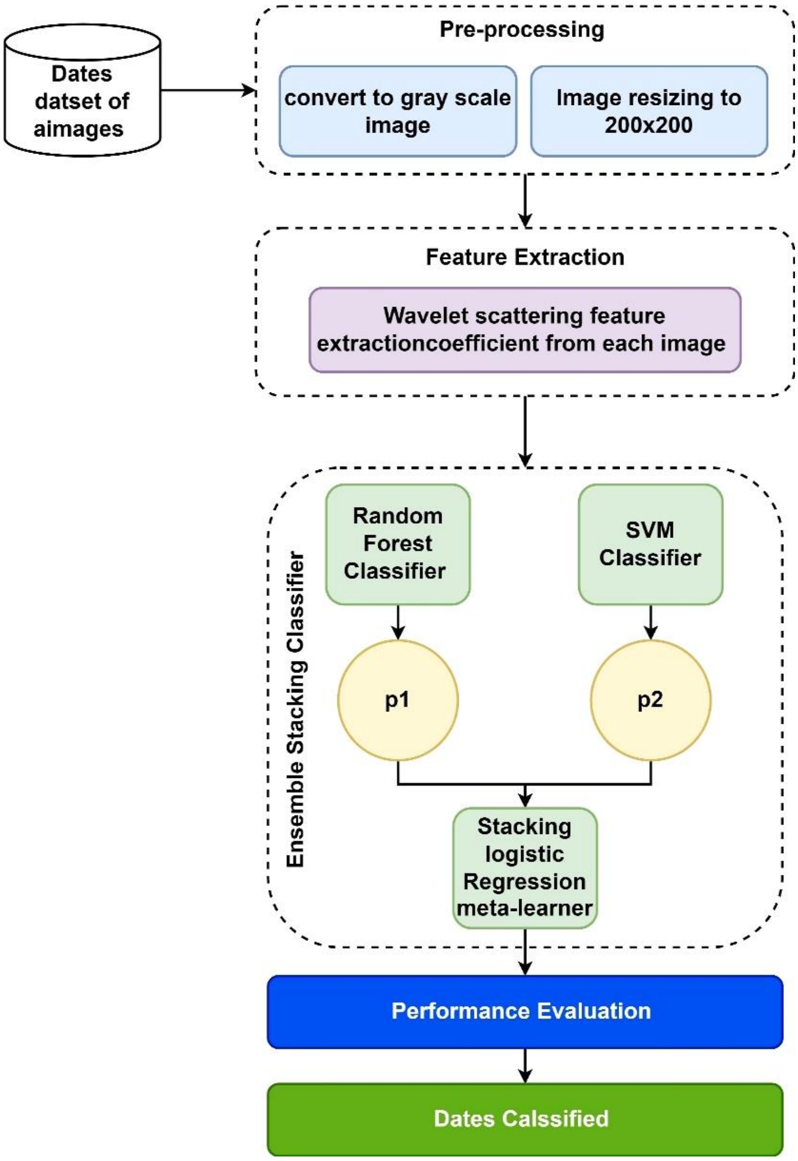


Figure 8. Block diagram of the proposed model of date fruit classification

7. Results and Discussion

To classify the date fruit in this study, a scattering wavelet transform was used to extract 10895 coefficients from each image. Prior to that, each image was pre-processed by converting it from the RGB color representation to grayscale images. Then, the images were resized to 200×200 pixels. The data was allotted 80% for training and 20% for testing. For the classification process, the RF and SVM were used and measured from a performance viewpoint. Then the stacking model was constructed by merging the RF and SVM with a meta-learner logistic regression model. The stacking classifier was then compared with both the RF and SVM. The performance was evaluated using a confusion matrix and ROC curves. The date classes were numbered in a confusion matrix as follows: Ajwa = 0, Glaxy = 1, Medjol = 2, Meniefi = 3, Nbat_ali = 4, Rutab = 5, Shaishi = 6, Sokari = 7, and Sugaey = 8. The experiments began by testing the RF classifier, where the number of estimators was 100. Table 2 and Figure 9 provide the performance of the RF model when classifying each date type. Despite the general accuracy of 0.84, the classifier shows high accuracy in classification. For some dates, like the Ajwa date type, accuracy reached 1.00. The variation in accuracy between date fruit classification returns is twofold. First, sometimes date fruit images do not contain smooth or regular patterns. This case is called a steering wavelet caused by images and date fruit that have abrupt changes inside the classification. For example, the precision in Table 2 is scaled between 0.67 to 1.00. The precision for Sugaey was 0.67, while the Agwa registered 1.00. The reason for high accuracy in predicting the Agwa date class is its unique texture type that yields a unique scattering coefficient, while the other classes achieved less than 0.92 because of the close texture between the nine classes.

Table 2. Performance table for RF classifier

Date class	Precision	Recall	F1-score	Support
Ajwa	1.00	1.00	1.00	44
Galaxy	0.84	0.84	0.84	32
Medjool	0.83	0.86	0.84	22
Meneifi	0.78	0.93	0.85	45
Nabat-Ali	0.84	0.76	0.80	42
Rutab	0.92	0.79	0.85	28
Shaishi	0.87	0.70	0.78	37
Sokeri	0.82	0.96	0.89	49
Sugaey	0.67	0.61	0.63	33
	Accuracy		**0.84**	

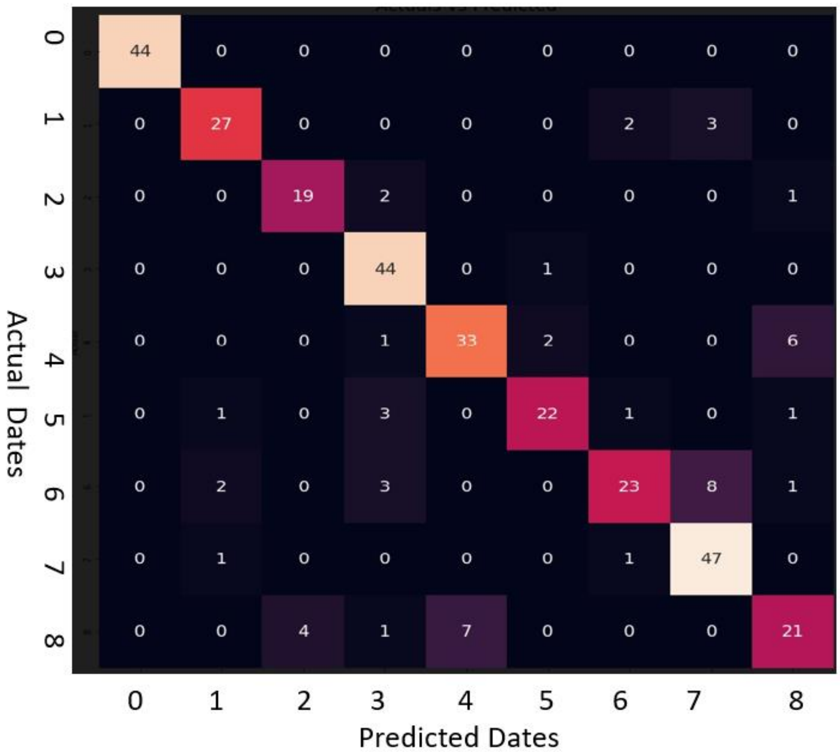


Figure 9. Random forest confusion matrix

The second dataset of Aiadi was used to test the wavelet scattering coefficient features with a random forest. The number of estimators was 100. Random forest achieved a macro-average accuracy of 0.95. The lowest precision was with Deglet due to the unbalanced nature of the dataset, as in Table 3 and the confusion matrix in Figure 10. In Table 3, the model achieved high overall accuracy because it always predicted the majority class. For example, Ajina, with 16 samples, scored 1.00 as precision, so the class with a high number of images is likely to be correct. In this model, Deglet scored high precision, while the number of samples was just seven. This result was due to the model having a small number of test sets—no more than 2 images in the test phase. Although the scattering wavelet needs a small number of samples for training, it is better to have more images to prove the generalization of the model in predicting a specific class.

Table 3. Performance table for RF classifier for Aiadi dataset

Date Class	Precision	Recall	F1-Score	Support
Adam Deglet Nour	1.00	1.00	1.00	14
Ajina	1.00	0.88	0.93	16
Bayd Hmam	0.94	0.88	0.91	17
Bouaarous	0.95	0.94	0.95	20
Degla Bayda	0.94	1.00	0.94	18
Deglet	1.00	0.86	0.92	7
Deglet Ghabia	1.00	1.00	1.00	5
Deglet Kahla	0.89	1.00	0.94	17
Dfar lgat	1.00	0.92	0.96	25
Dgoul	1.00	0.95	0.98	22
Ghars	1.00	1.00	1.00	13
Hamraya	1.00	0.86	0.92	14
Loullou	0.93	1.00	0.96	13
Tanslit	0.81	1.00	0.90	13
Tantbucht	1.00	0.95	0.97	19
Tarmount	0.80	1.00	0.89	16
Techbeh Tati	1.00	0.92	0.96	26
Tinisin.	1.00	0.95	0.98	22
Tivisyaouin	1.00	1.00	1.00	9
	Accuracy		**0.95**	

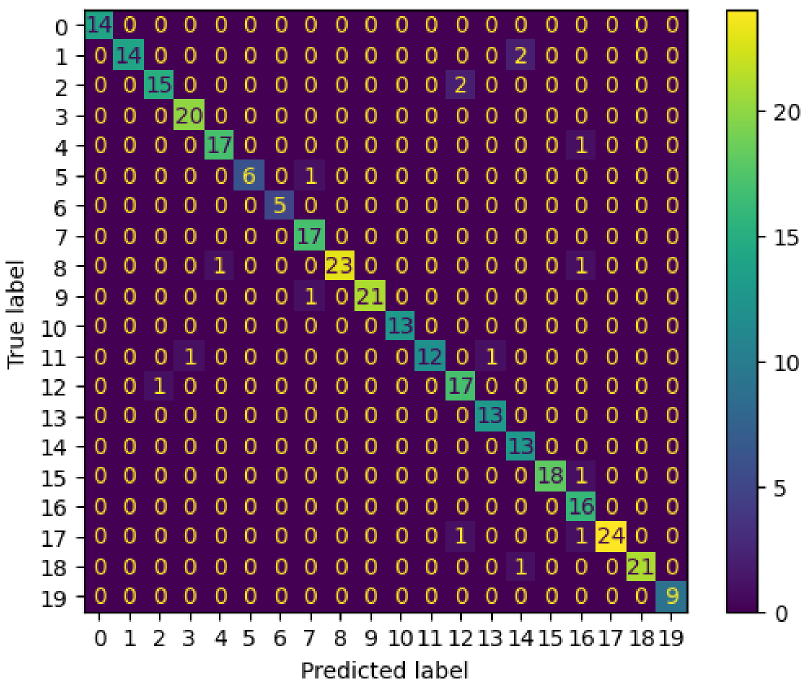


Figure 10. Random forest confusion matrix for Aiadi dataset

The second model to be tested was the linear SVM. The hyperparameter of the penalty rate c was accomplished by the operating range of c values over SVM using grid search. The best c was 0.01, which yielded the highest performance accuracy of 0.92. The SVM model achieved higher accuracy than the RF because the dataset was small with high dimensionality. RF can face overfitting in small datasets, especially when dealing with many scattering coefficients as feature sets. In contrast, SVM can be more efficient with a limited dataset because SVM tends to be more efficient in a high-dimensional setting when the number of data points is enough to define the margin. Table 4 shows the precision and recall of predicting each date fruit class, and Figure 11 presents the confusion matrix.

Table 4. Performance table for SVM classifier

Date class	Precision	Recall	F1-score	Support
Ajwa	1.00	1.00	1.00	44
Galaxy	0.97	0.88	0.92	32
Medjool	0.95	0.86	0.90	22
Meneifi	0.79	1.00	0.88	45
Nabat-Ali	0.97	0.86	0.91	42
Rutab	0.96	0.82	0.88	28
Shaishi	0.92	0.92	0.92	37
Sokeri	0.94	0.96	0.95	49
Sugaey	0.82	0.85	0.84	33
Accuracy			**0.92**	**332**

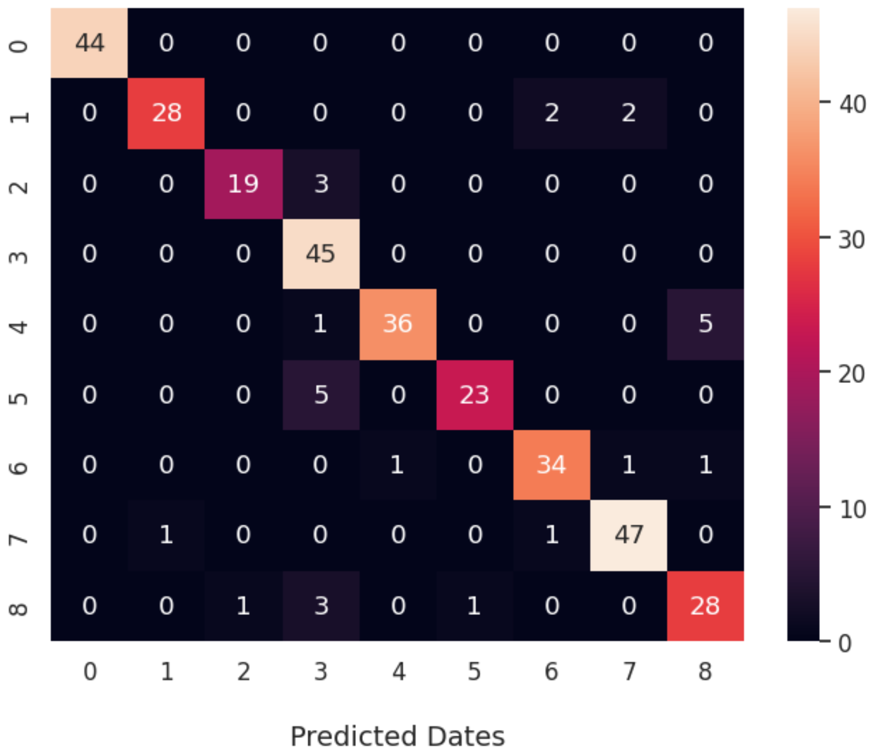


Figure 11. SVM confusion matrix

Linear SVC with a c rate of 0.01 was tested with the second dataset. The results of the test are in Table 5 and Figure 12. The SVC achieved an accuracy of 0.93. Again, Tanslit class prediction was the lowest in precision, about 0.69, while Techbeh Tati and Tinisin registered precision, reaching 1.0. In the second dataset, the SVM did not perform as well as in the first dataset because the dimensionality of the scattering coefficient of 20 date fruit classes was too high. The high dimensionality of the data with some overlapped features between date fruit classes may cause the data to be unclear and inseparable.

Table 5. Performance table for SVM classifier for the second dataset.

	Date Class	Precision	Recall	F1-Score	Support
0	Adam Deglet Nour	0.93	1.00	0.97	14
1	Ajina	0.94	1.00	0.97	16
2	Bayd Hmam	0.94	0.94	0.94	17
3	Bouaarous	0.95	0.90	0.92	20
4	Degla Bayda	0.94	0.94	0.94	18
5	Deglet	1.00	0.71	0.83	7
6	Deglet Ghabia	0.80	0.80	0.80	5
7	Deglet Kahla	0.94	1.00	0.97	17
8	Dfar lgat	1.00	1.00	1.00	25
9	Dgoul	0.96	1.00	0.98	22
10	Ghars	0.93	1.00	0.96	13
11	Hamraya	0.92	0.86	0.89	14
12	Litima	0.89	0.94	0.92	18
13	Loullou	0.93	1.00	0.96	13
14	Tanslit	0.69	0.85	0.76	13
15	Tantbucht	1.00	0.95	0.97	19
16	Tarmount	0.88	0.94	0.91	16
17	Techbeh Tati	1.00	0.88	0.94	26
18	Tinisin.	1.00	0.82	0.90	22
19	Tivisyaouin	0.80	0.89	0.84	9
Accuracy			**0.92**		**324**

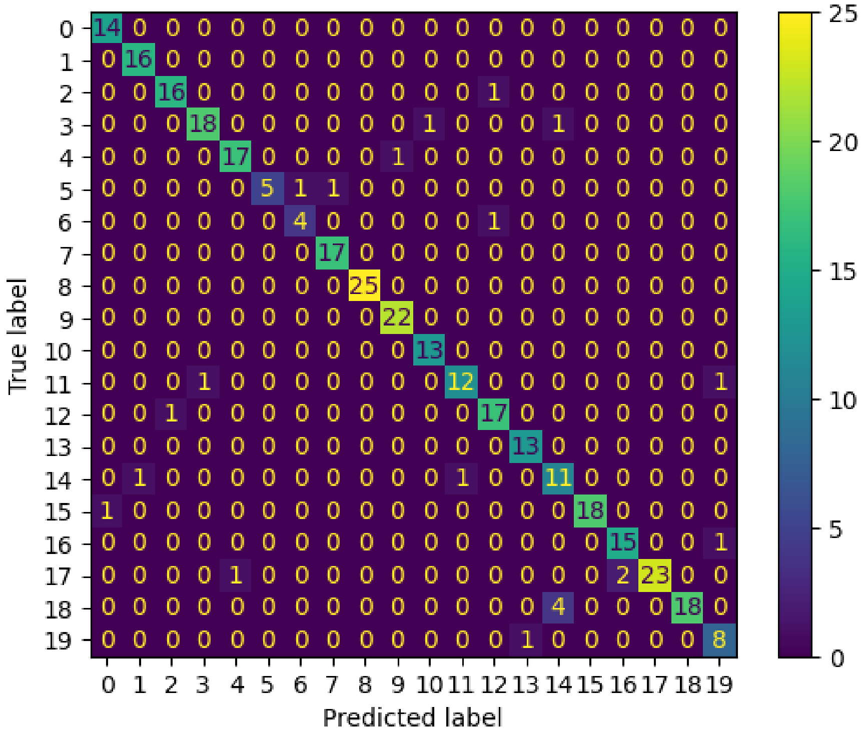


Figure 12. SVM confusion matrix for Aiadi dataset

The third model is the classification of the stacking Ensemble Model. The stacking classifier consisted of two local learners (RF and SVM). The predictions of local learners are used to train the meta-learner, which is a logistic regression model. Stacking models show a preponderance over the two previous models (RF and SVM) separately. The efficiency of stacking appears clearly from the values in Table 6 and the confusion matrix in Figure 13. The accuracy is 0.99 for the stacking classification model.

Table 6. Performance table for stacking classifier

Date class	Precision	Recall	F1-score	Support
Ajwa	1.00	1.00	1.00	45
Galaxy	1.00	0.97	0.98	32
Medjool	0.95	0.95	0.95	22
Meneifi	0.96	1.00	0.98	45
Nabat-Ali	1.00	1.00	1.00	41
Rutab	1.00	0.97	0.98	29
Shaishi	1.00	1.00	1.00	37
Sokari	0.98	1.00	0.99	49
Sugaey	1.00	0.97	0.98	33
Accuracy			**0.99**	

According to the confusion matrix, Ajwa is the date class with the highest classification success in all models. In contrast, the Medjool class and Meneifi class were always at lower rates compared to the other classes in all three models. The stacking model outperforms SVM and RF separately in this dataset because stacking allows both SVM and RF to learn from each other. So, the hyper-learner combines insights to make better predictions. Table 6 registered 0.99 as the general accuracy for the stacking model for the first Kaggle dataset. In contrast, the accuracies for the same dataset were 0.84 and 0.95 for both RF and SVM, respectively. These results refer to the leveraging of the efficiency of scattering wavelets as discriminative features by using stacking as a classifier model.

The third stacking classifier was tested with the Aiadi dataset and scored the highest with a macro-average accuracy of 0.98. Stacking achieved stable results within all classes, as in Table 7 and Figure 13, in terms of precision, recall, and f-score.

Table 7. Performance table for stacking classifier for Aiadi dataset

Date Class	Precision	Recall	F1-Score	Support
Adam Deglet Nour	1.00	1.00	1.00	14
Ajina	1.00	0.94	0.97	16
Bayd Hmam	1.00	0.94	0.97	17
Bouaarous	1.00	0.90	0.95	20
Degla Bayda	1.00	1.00	1.00	18
Deglet	1.00	1.00	1.00	7
Deglet Ghabia	1.00	1.00	1.00	5
Deglet Kahla	1.00	1.00	1.00	17
Dfar lgat	1.00	1.00	1.00	25
Dgoul	1.00	1.00	1.00	22
Ghars	1.00	1.00	1.00	13
Hamraya	1.00	1.00	1.00	14
Litima	0.95	1.00	0.97	18
Loullou	1.00	1.00	1.00	13
Tanslit	0.87	1.00	0.93	13
Tantbucht	1.00	0.95	0.97	19
Tarmount	0.89	1.00	0.94	16
Techbeh Tati	1.00	0.92	0.96	26
Tinisin	0.92	1.00	0.96	22
Tivisyaouin	1.00	1.00	1.00	9
Accuracy		**0.98**		**324**

Despite the high number of classes and the differentiation in the number of images between the classes, using scattering wavelet features with a stacking ensemble classifier achieved firm performance.

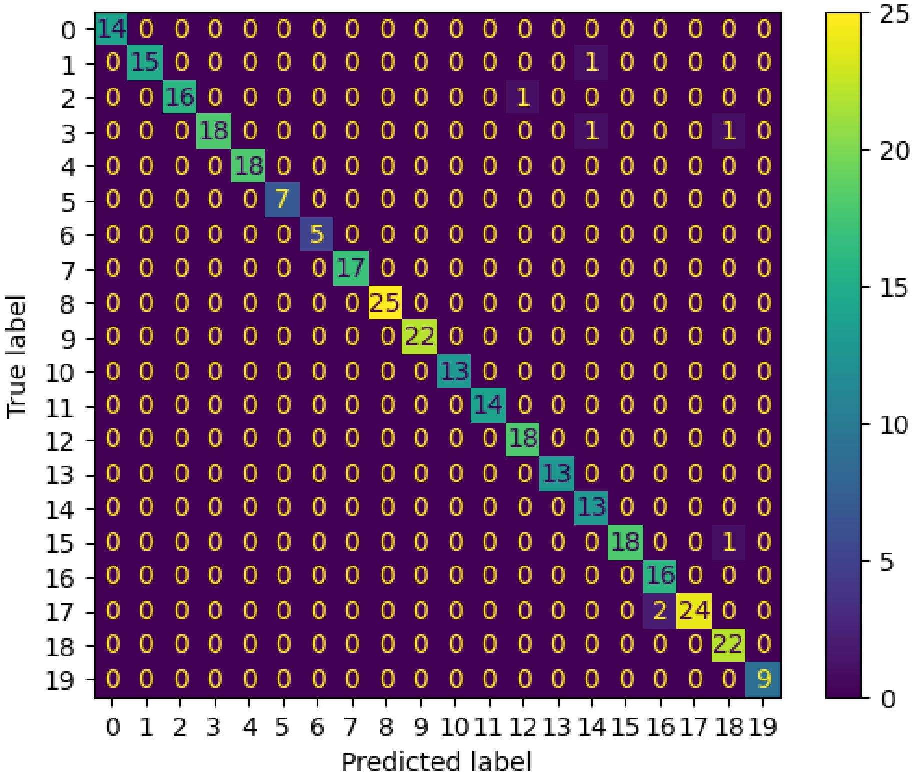
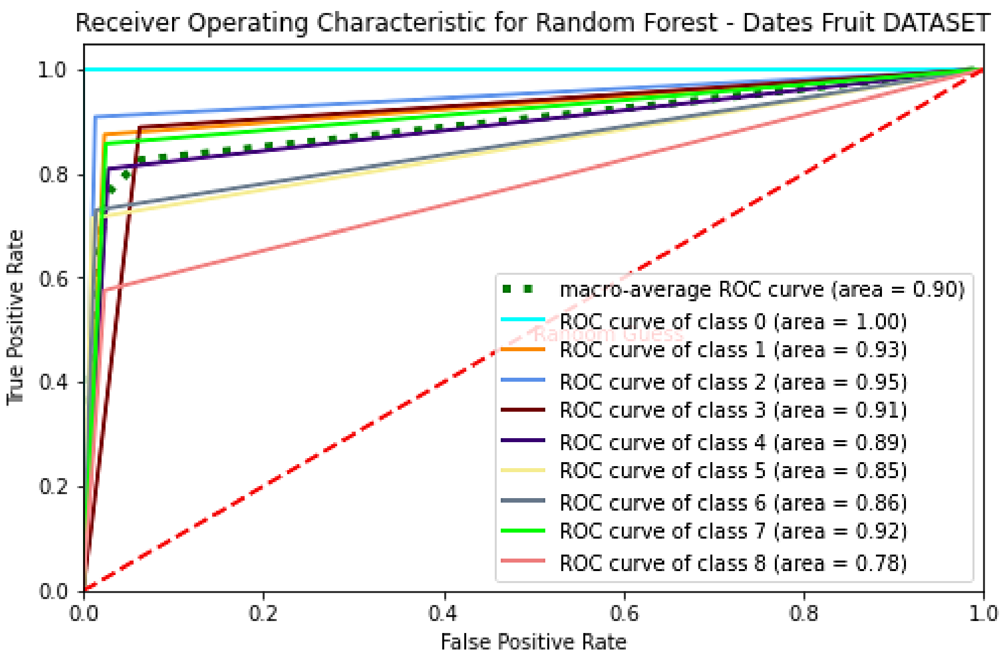
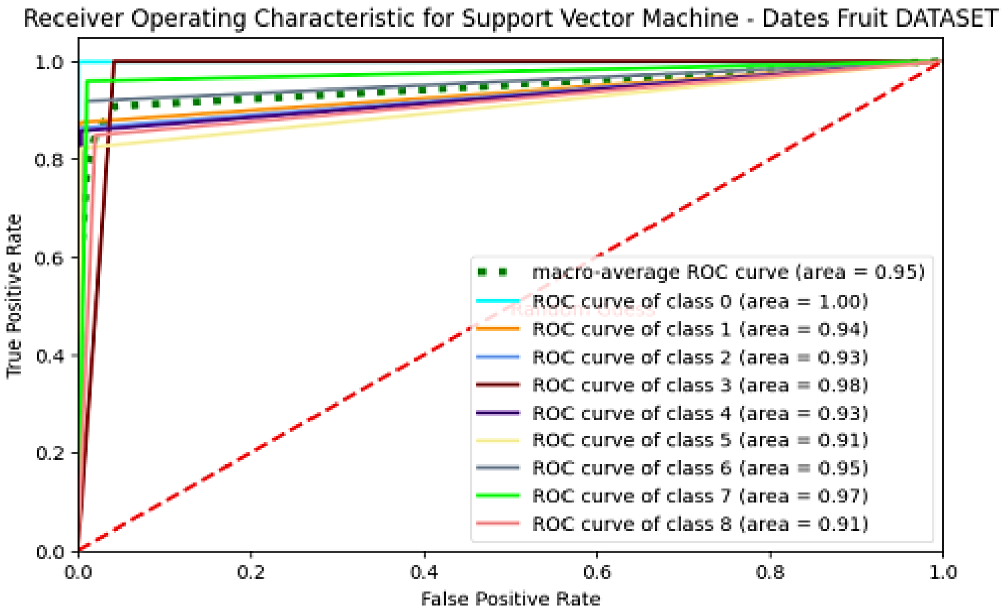


Figure 13. Random forest confusion matrix for Aiadi dataset

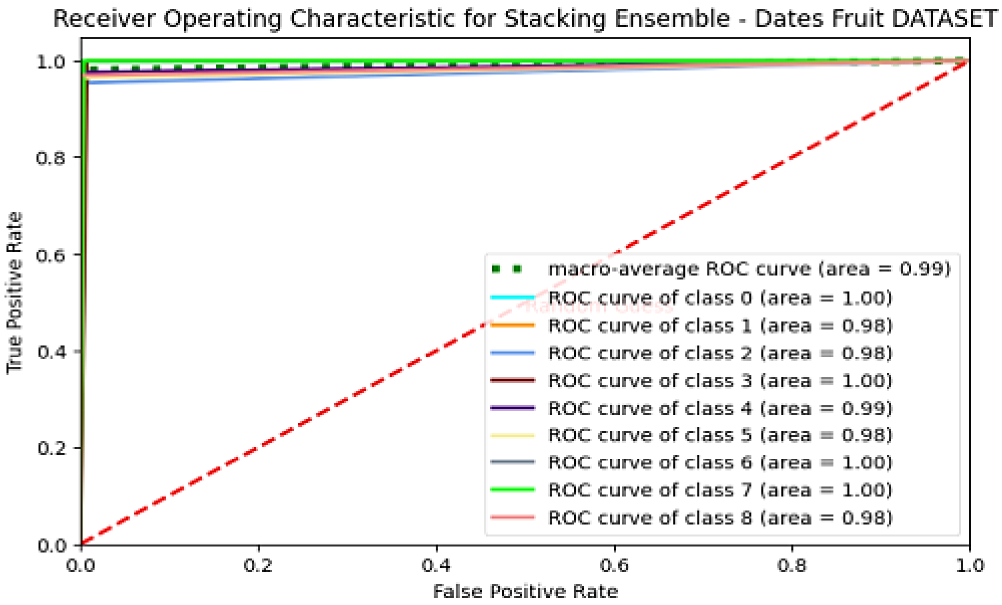
Aiadi et al. relied on the fusion of the Principal Component Analysis (PCA) and Visual Geometry Group (VGG) features into one feature set. The extracted features were fed into KNN, SVM, and DT classifiers. The DT classifier achieved 0.93 accuracy, KNN registered 0.97 accuracy, and SVM achieved 0.99 accuracy, despite the Degla Bayda class achieving only 0.65 accuracy. The Litima date class also recorded an accuracy of 0.85. Accordingly, Aiadi et al.'s proposed model has wiggles in some classes. In contrast, our proposed model, which depends on wavelet scattering features, appeared more robust and stable in predicting all classes.



(a)



(b)



(c)

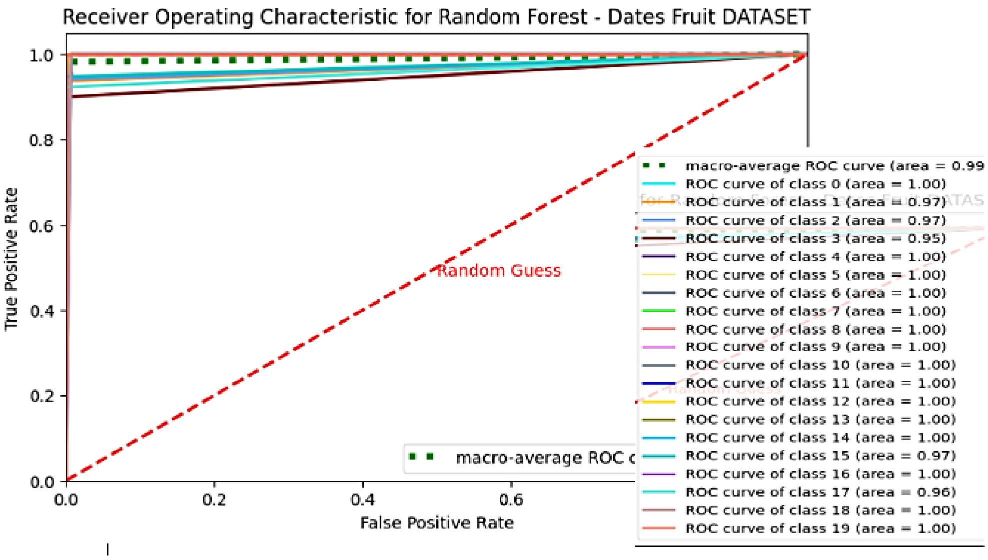
Figure 14. ROC curves (a) Random Forest, (b) SVM, (c) Stacking ensemble

The ROC_AUC curve of RF obtained for each date fruit class is offered in Figure 14(a). The performance of the RF model was moderate in predicting some classes, while the ROC curve for SVM in Figure 14(b) shows that the prediction rate of most classes becomes closer to the upper left corner of the plot. This means the ratio of TP to FP has increased. Last, in Figure 14(c), it is noticeable that most of the classes' curves are in the upper left corner, which confirms that all classes predicted high performance with evidence of a high TP rate to the FP rate.

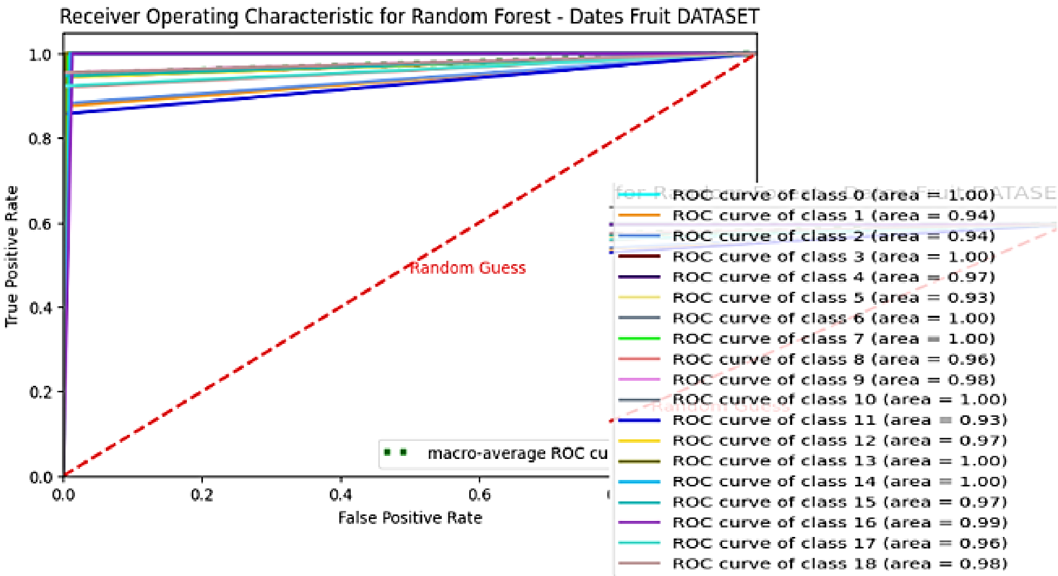
The stacking model shows high performance in classifying the date fruits because of its learning behavior. The stacking learning paradigm relies on a learning meta-model that learns from an internal classifier, which is the reason for the absence of overfitting in ensemble models. Stacking models also helps in avoiding model selection overhead, which is the process of choosing the most efficient model among the various models.

Using stacking classifiers with scattering coefficients is more suitable than deep dense classifiers that need tuning of hyper-parameters and work effectively on big datasets. The scattering wavelet acts as an efficient discriminative feature that succeeded in classifying the date fruit with close texture patterns even when the dataset is small to moderate in size.

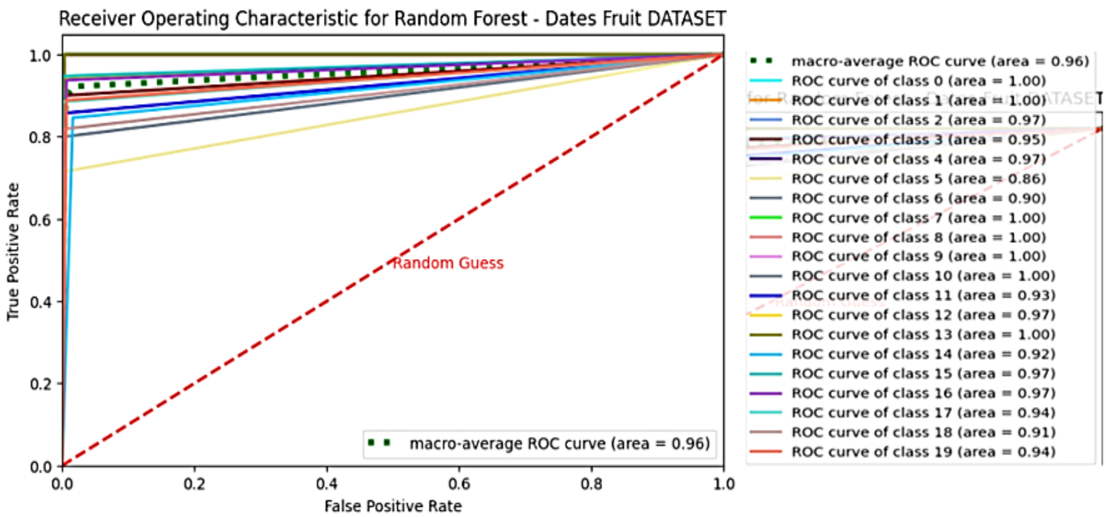
In the ROC-AUC curves for the second dataset, both the RF and SVM classifiers show moderate performance in predicting some classes. In Figure 15, for the RF for the classes Ajina and _Adam Deglet Nour, the ROC covered 0.94, while for the SVM classes of Deglet Kahla, which is class number 5, the ROC value was 0.86. While stacking ROC-AUC for some classes, like Deglet Ghabia, registered at least 0.96 of the area.



(a)



(b)



(c)

Figure 15. ROC curves (a) Random Forest, (b) SVM and (c) Stacking ensemble for Aiadi dataset

Consequently, it can be said that higher classification success is attained in comparison with other studies using equivalent datasets, see Table 8. To summarize, our method achieved a high result and accuracy of classification when the number of images in the training data was 70% and the best accuracy when the training data was 80%. To be able to enhance the average classification success to the 100% level, more images are required. In future studies, it is predicted that classification success will increase through more date fruit images.

Table 8. Methods comparing with their accuracy

Reference	Image Total	Accuracy
[20]	325	73%
[23]	500	89.2%
[7]	3228	97.21%
[22]	450	98%
[2]	800	98%
Our method	1658	99%

The success of the proposed model over the previous research relates to the use of a scattering wavelet to extract discriminative features. This type of wavelet transform that can extract the low frequencies of the texture pattern has proven itself in the experiment as an efficient feature.

CNN models may struggle to classify fruits if the images are close to each other in shape, texture, and color. Even the complex CNN models might fail to classify fruits in the case of small datasets. Therefore, the scattering wavelet feature succeeded in the two tested datasets because it minimized the class differences while preserving discriminability between dataset classes. The number of images in each class is not high in the test datasets. So, scattering wavelet features are more effective as a discriminative feature. Also, we choose scattering wavelets instead of RGB images because fruit images are affected by lightning conditions and camera angles, making the extracted features unstable, less informative, and less meaningful for any classifier, especially for small datasets.

RF and SVM are often used with stacking combinations because the two algorithms can improve each other's efficiency. RF efficiently classifies data with many features, while SVM is reasonable for high-dimensional non-linear data. As a result, the combination of RF and SVM through the stacking approach creates a robust model that performs better than either model alone.

8. Conclusion

Dates are one of the essential ancient fruits that play a vital role in the modern diets of several nations. They have a large global market and significant economic importance due to their versatility, enabling them to be transformed into many different products. Many researchers have tested various directions to design a framework for detecting date fruit classes. Some used machine learning models with features like the color and shape of the date fruit. Others used modern deep learning models like CNN.

Consequently, all paradigms that depended on the shape or color faced the overlapping of features between the date fruit classes. As a result, this research tried to find another paradigm that uses texture features as numeric coefficients with a machine-learning classifier. Our proposed model is capable of classifying date fruit without the need for time-consuming and complicated physical measurements. The scattering wavelet shows efficiency in date fruit texture analysis by extracting the discriminative features for each date fruit type. Scattering analysis of texture shows superiority over other features like shape and color to classify date fruit. Because the shape and color features may be common in many classes of date fruit, both mentioned features cannot be reliable for this target. The dominance of the proposed paradigm is reflected in the results, which show an efficient classifier tested with two benchmarked datasets. Scattering the coefficient of date fruit tissue with a stacking classifier was efficient and better than using separated machine learning models. This research highlighted the importance of the texture, or tissue, of the fruit as a successful feature that can be used to distinguish between date fruit classes.

There are two scattering wavelet limitations. First, converting the texture of the date class into numeric features as well as decomposing and reconstructing signals of the date fruit texture consume time. So, this can make the scattering wavelet feature limited in real-time applications. Second, selecting the degree of decomposition of the scattering feature can be complex and needs to be tested. In future work, scattering wavelet texture will be used to classify the maturity rating of other fruits. Also, the scattering wavelet paradigm has to be optimized for the aspect of time.

9. Declarations

9.1. Author Contributions

Conceptualization, A.A.A. and A.B.A.A.; methodology, A.A.A.; software, A.B.A.A.; validation, V.S.; formal analysis, V.S.; investigation, A.B.A.A.; resources, A.A.A.; writing—original draft preparation, A.B.A.A. and V.S.; writing—review and editing, V.S.; visualization, A.B.A.A.; supervision, A.A.A.; project administration, A.A.A.; funding acquisition, A.A.A. All authors have read and agreed to the published version of the manuscript.

9.2. Data Availability Statement

The data presented in this study are available in the article.

9.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

9.4. Institutional Review Board Statement

Not applicable.

9.5. Informed Consent Statement

Not applicable.

9.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

10. References

[1] Albarrak, K., Gulzar, Y., Hamid, Y., Mehmood, A., & Soomro, A. B. (2022). A Deep Learning-Based Model for Date Fruit Classification. Sustainability (Switzerland), 14(10), 6339. doi:10.3390/su14106339.

[2] Muhammad, G. (2015). Date fruits classification using texture descriptors and shape-size features. Engineering Applications of Artificial Intelligence, 37, 361–367. doi:10.1016/j.engappai.2014.10.001.

[3] Haidar, A., Dong, H., & Mavridis, N. (2012). Image-based date fruit classification. International Congress on Ultra-Modern Telecommunications and Control Systems and Workshops, 357–363. doi:10.1109/ICUMT.2012.6459693.

[4] Alharbi, K. L., Raman, J., & Shin, H. J. (2021). Date fruit and seed in nutricosmetics. Cosmetics, 8(3), 59. doi:10.3390/cosmetics8030059.

[5] Khayer, M. A., Hasan, M. S., & Sattar, A. (2021). Arabian date classification using CNN algorithm with various pre-trained models. Proceedings of the 3rd International Conference on Intelligent Communication Technologies and Virtual Mobile Networks, ICICV 2021, 1431–1436. doi:10.1109/ICICV50876.2021.9388413.

[6] Muhammad, G. (2014). Automatic date fruit classification by using local texture descriptors and shape-size features. Proceedings - UKSim-AMSS 8th European Modelling Symposium on Computer Modelling and Simulation, EMS 2014, 174–179. doi:10.1109/EMS.2014.63.

[7] Alsirhani, A., Siddiqi, M. H., Mostafa, A. M., Ezz, M., & Mahmoud, A. A. (2023). A Novel Classification Model of Date Fruit Dataset Using Deep Transfer Learning. Electronics (Switzerland), 12(3), 665. doi:10.3390/electronics12030665.

[8] Nasiri, A., Taheri-Garavand, A., & Zhang, Y. D. (2019). Image-based deep learning automated sorting of date fruit. Postharvest Biology and Technology, 153, 133–141. doi:10.1016/j.postharvbio.2019.04.003.

[9] Momeny, M., Jahanbakhshi, A., Jafarnezhad, K., & Zhang, Y. D. (2020). Accurate classification of cherry fruit using deep CNN based on hybrid pooling approach. Postharvest Biology and Technology, 166, 111204. doi:10.1016/j.postharvbio.2020.111204.

[10] Zhang, D., Lee, D. J., Tippetts, B. J., & Lillywhite, K. D. (2014). Date maturity and quality evaluation using color distribution analysis and back projection. Journal of Food Engineering, 131, 161–169. doi:10.1016/j.jfoodeng.2014.02.002.

[11] Ammari, A. C., Khriji, L., & Awadalla, M. (2020). HW/SW Co-'esign for Dates Classification on Xilinx Zynq SoC. Conference of Open Innovation Association, FRUCT, 2020-April, 10–15. doi:10.23919/FRUCT48808.2020.9087548.

[12] Altaheri, H., Alsulaiman, M., & Muhammad, G. (2019). Date Fruit Classification for Robotic Harvesting in a Natural Environment Using Deep Learning. IEEE Access, 7, 117115–117133. doi:10.1109/ACCESS.2019.2936536.

[13] Ishikawa, T., Hayashi, A., Nagamatsu, S., Kyutoku, Y., Dan, I., Wada, T., Oku, K., Saeki, Y., Uto, T., Tanabata, T., Isobe, S., & Kochi, N. (2018). Classification of strawberry fruit shape by machine learning. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives, 42(2), 463–470. doi:10.5194/isprs-archives-XLII-2-463-2018.

[14] Rybacki, P., Niemann, J., Derouiche, S., Chetehouna, S., Boulaares, I., Seghir, N. M., Diatta, J., & Osuch, A. (2024). Convolutional Neural Network (CNN) Model for the Classification of Varieties of Date Palm Fruits (Phoenix dactylifera L.). Sensors, 24(2), 558. doi:10.3390/s24020558.

[15] Fadel, M. (2007). Date fruits classification using probabilistic neural networks. Agricultural Engineering International: CIGR Journal, 9, 1-11.

[16] M.Alrajeh, K., & A. A. Alzohairy, T. (2012). Date Fruits Classification using MLP and RBF Neural Networks. International Journal of Computer Applications, 41(10), 36–41. doi:10.5120/5579-7686.

[17] Sahidullah, M., Nayan, N. M., Morshed, M. S., Hossain, M. M., & Islam, M. U. (2023). Date Fruit Classification with Machine Learning and Explainable Artificial Intelligence. International Journal of Computer Applications, 184(50), 1–5. doi:10.5120/ijca2023922617.

[18] ÖZALTIN, Ö. (2024). Date Fruit Classification by Using Image Features Based on Machine Learning Algorithms. Research in Agricultural Sciences, 55(1), 26–35. doi:10.5152/auaf.2024.23171.

[19] Ghazal, S., Qureshi, W. S., Khan, U. S., Iqbal, J., Rashid, N., & Tiwana, M. I. (2021). Analysis of visual features and classifiers for Fruit classification problem. Computers and Electronics in Agriculture, 187, 106267. doi:10.1016/j.compag.2021.106267.

[20] Abi Sen, A. A., Bahbouh, N. M., Alkhodre, A. B., Aldhawi, A. M., Aldham, F. A., & Aljabri, M. I. (2020). A classification algorithm for date fruits. Proceedings of the 7th International Conference on Computing for Sustainable Global Development, INDIACom 2020, 235–239. doi:10.23919/INDIACom49435.2020.9083706.

[21] Koklu, M., Kursun, R., Taspinar, Y. S., & Cinar, I. (2021). Classification of Date Fruits into Genetic Varieties Using Image Analysis. Mathematical Problems in Engineering, 2021, 1–13. doi:10.1155/2021/4793293.

[22] Noutfia, Y., & Ropelewska, E. (2023). Innovative Models Built Based on Image Textures Using Traditional Machine Learning Algorithms for Distinguishing Different Varieties of Moroccan Date Palm Fruit (Phoenix dactylifera L.). Agriculture (Switzerland), 13(1), 26. doi:10.3390/agriculture13010026.

[23] Magsi, A., Ahmed Mahar, J., & Danwar, S. H. (2019). Date Fruit Recognition using Feature Extraction Techniques and Deep Convolutional Neural Network. Indian Journal of Science and Technology, 12(32), 1–12. doi:10.17485/ijst/2019/v12i32/146441.

[24] Almomen, M., Al-Saeed, M., & Ahmad, H. F. (2023). Date Fruit Classification Based on Surface Quality Using Convolutional Neural Network Models. Applied Sciences (Switzerland), 13(13), 7821. doi:10.3390/app13137821.

[25] Alhamdan, W. S. N., & Howe, J. M. (2021). Classification of Date Fruits in a Controlled Environment Using Convolutional Neural Networks. Advances in Intelligent Systems and Computing, 1339, 154–163. doi:10.1007/978-3-030-69717-4_16.

[26] Al-Sabaawi, A., Hasan, R. I., Fadhel, M. A., Al-Shamma, O., & Alzubaidi, L. (2021). Employment of Pre-trained Deep Learning Models for Date Classification: A Comparative Study. Intelligent Systems Design and Applications: 20th International Conference on Intelligent Systems Design and Applications (ISDA 2020), December 12-15, 2020, 181–189. doi:10.1007/978-3-030-71187-0_17.

[27] Alresheedi, K. M., Aladhadh, S., Khan, R. U., & Qamar, A. M. (2022). Dates fruit recognition: From classical fusion to deep learning. Computer Systems Science and Engineering, 40(1), 151–166. doi:10.32604/CSSE.2022.017931.

[28] Ibrahim, D. M., & Elshennawy, N. M. (2022). Improving Date Fruit Classification Using CycleGAN-Generated Dataset. CMES - Computer Modeling in Engineering and Sciences, 130(3), 331-348. doi:10.32604/cmes.2022.016419.

[29] Nadhif, M. F., & Dwiasnati, S. (2023). Classification of Date Fruit Types Using CNN Algorithm Based on Type. MALCOM: Indonesian Journal of Machine Learning and Computer Science, 3(1), 36–42. doi:10.57152/malcom.v3i1.724.

[30] Faisal, M., Alsulaiman, M., Arafah, M., & Mekhtiche, M. A. (2020). IHDS: Intelligent harvesting decision system for date fruit based on maturity stage using deep learning and computer vision. IEEE Access, 8, 167985–167997. doi:10.1109/ACCESS.2020.3023894.

[31] Indriani, O. R., Kusuma, E. J., Sari, C. A., Rachmawanto, E. H., & Setiadi, D. R. I. M. (2017). Tomatoes classification using K-NN based on GLCM and HSV color space. Proceedings - 2017 International Conference on Innovative and Creative Information Technology: Computational Intelligence and IoT, ICITech 2017, 2018-January, 1–6. doi:10.1109/INNOCIT.2017.8319133.

[32] Mallat, S. (2012). Group Invariant Scattering. Communications on Pure and Applied Mathematics, 65(10), 1331–1398. doi:10.1002/cpa.21413.

[33] Bruna, J., & Mallat, S. (2013). Invariant scattering convolution networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(8), 1872–1886. doi:10.1109/TPAMI.2012.230.

[34] Aiadi, O., Khaldi, B., Kherfi, M. L., Mekhalfi, M. L., & Alharbi, A. (2022). Date Fruit Sorting Based on Deep Learning and Discriminant Correlation Analysis. IEEE Access, 10, 79655–79668. doi:10.1109/ACCESS.2022.3194550.

[35] Jin, Y., & Duan, Y. (2020). Wavelet scattering network-based machine learning for ground penetrating radar imaging: Application in pipeline identification. Remote Sensing, 12(21), 1–24. doi:10.3390/rs12213655.

[36] Soro, B., & Lee, C. (2019). A wavelet scattering feature extraction approach for deep neural network based indoor fingerprinting localization. Sensors (Switzerland), 19(8), 1790. doi:10.3390/s19081790.

[37] Mienye, I. D., & Sun, Y. (2022). A Survey of Ensemble Learning: Concepts, Algorithms, Applications, and Prospects. IEEE Access, 10, 99129–99149. doi:10.1109/ACCESS.2022.3207287.

[38] Kumar, M., Singhal, S., Shekhar, S., Sharma, B., & Srivastava, G. (2022). Optimized Stacking Ensemble Learning Model for Breast Cancer Detection and Classification Using Machine Learning. Sustainability (Switzerland), 14(21), 13998. doi:10.3390/su142113998.

[39] Taspinar, Y. S., Cinar, I., & Koklu, M. (2022). Classification by a stacking model using CNN features for COVID-19 infection diagnosis. Journal of X-Ray Science and Technology, 30(1), 73–88. doi:10.3233/XST-211031.

[40] Alhamdan, W. S. N. (2024). Date Fruit Image Dataset in Controlled Environment: Single date fruit images taken in a controlled environment. Available online: https://www.kaggle.com/datasets/wadhasnalhamdan/date-fruit-image-dataset-in-controlled-environment?resource=download (accessed on March 2024).