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Classification of Dates (*Phoenix Dactylifera L.*) Varieties Using Texture Feature Analysis

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Abstract: The Date Palm (Phoenix dactylifera L.) is an ancient evergreen fruit tree. It belongs to the palm family Phoenix (Arecaceae). Dates are Pakistan's 3rd most important fruit crop, after mangos and citrus. Almost 325 different varieties of date fruit are grown in several parts of Pakistan. Visual perception makes it difficult to classify dates by looking at their fruits. The best determinant for date classification is the external appearance of the fruits. Their varietal classification is crucial for meeting consumer and market expectations in terms of quality. By automating processes like fruit classification, machine learning (ML) has transformed the fruit-producing business. The excellent performance of CNNs in image categorization has increased productivity and efficiency overall. The goal of the research is to develop an automated framework for the classification of date fruits using the deep learning technique based on texture feature analysis. For evaluation purposes, a date fruit image dataset of 1200 images have developed. Four types of date fruits were chosen for experiments, namely Aseel, Karbala, Muzawati, and Zahedi. Their images were captured, with 80% being utilized for the training dataset and 20% being used for testing. Experiments were carried out on the chosen date fruit varieties by the defined framework. The CNN models Inception V3, VGG16, and VGG19 were used as classifiers. Other ML classifiers like KNN and SVC were also deployed. CNN, on the other hand, outperformed all others with 99.44 percent accuracy across 10 epochs.

Keywords: Texture; Feature Analysis; Transfer Learning; Features Optimization; CNN; Inception V3; VGGs Network.

1. Introduction

Food is considered a basic human need that can be met through agriculture. Agriculture is Pakistan's leading economic activity, with a 26% contribution to the gross domestic product. Digital farming, often known as "digital agriculture," is a new scientific subject that employs data and machine learning [1, 2]. The Date Palm (Phoenix dactylifera L.) is an evergreen ancient fruit tree on the earth [3]. Dates are a delicious, sweet-tasting fruit that grows in many countries around the world. It is primarily produced in South Africa and the Middle East [4]. The archaeological site of Mohenjo-Daro (Larkana, Sindh) found date palms, indicating that dates were cultivated in Sindh 5,000 years ago. Date palm cultivation in Pakistan dates back to the days of the Sind civilization [5]. Pakistan is the only country in South Asia that grows date fruits commercially. Dates are Pakistan's 3rd most important fruit crop, after mango and citrus of Pakistan's. Due to the different soils and seasons, Pakistan is an ideal place for the production and cultivation of dates [6].

Sindh province is the largest producer of date palm. Dates are cultivated in all four provinces of Pakistan. The Oases of Baluchistan and the Punjabi irrigated plains are the main hubs of the date palm business. Date fruit has such characteristics that are useful in classification. In the 2017-18 season, Pakistan produced 540606 tons of dates from 98415 ha, with an average yield of 5.5 t/ha. Sindh and Baluchistan are the two provinces that produce the most dates in Pakistan. The third and fourth largest producers in the nation, respectively, are Punjab and Khyber Pakhtunkhwa. Pakistan is one of the top exporting countries for dates. India, France, the United States, Germany, and the United Kingdom are the top five countries importing dates. [7].

The date palm tree offers numerous advantages to rural Pakistani populations. The tree's wood is chopped and used as fuel, as well as for the construction of houses and the creation of artifacts. Fruit baskets and mats are woven from palm leaflets and fronds, respectively [5].

Fruit classification is becoming more popular in image-processing applications, particularly in the agricultural field. Various illuminations produce different intensities on the surface of the item, resulting in incorrect classification. The focus of this research is on improving the creation of classification models for photographs collected in natural settings [8]. Three CNN models are used to classify date fruits and date palm leaves. Using optimum tuning and a solid feature set, traditional machine learning could produce improved classification performance that is comparable to that provided by deep learning [9-11]. A smart harvesting decision system has been developed using computer vision to forecast the date (type, maturity level, and weight). The framework uses three classification models to classify photographs of date fruits in real-time. It gives a unique dataset of 1658 high-resolution photographs for use in computer vision [12-14]. Images dataset were used to collect a total of 34 attributes, including morphological characteristics, form, and colour. A model was created using the logistic regression and artificial neural networks [15]. According to the findings, machine learning systems can accurately classify date fruit types. An automatic date fruit classification approach was developed using pattern recognition and computer vision. Image processing involves various phases, including masking, filtering, and region identification, to extract features. An automatic classification system for Oman dates fruit types has been developed. 600 samples of Oman dates were chosen and photographed individually. The highest classification accuracy, 97.26 percent, is attained using a combination of 15 colour and shape-size parameters [16]. Using colour, shape, size, and texture features, and this work automatically categorises six different date kinds, cutting down on manual categorization time and improving date quality. Results utilising 15 features and seven tan-sigmoid neurons demonstrate hidden layer accuracy, recall, and precision of 99.2 percent, 99.12 percent, and 99.25 percent [17]. Neural networks received 87.5 percent and 91.1 percent MLP recognition by backpropagation and RBF, respectively, according to performance tests, consistent with the best findings published in the same data source and testing standards [18].

Dates offer a variety of fascinating properties that might help you recognize and identify a specific date type. SVM was used to develop a system to classify which dates are edible and which ones are non-nutritious by analyzing their appearance and texture [19]. Four parameters are utilized to evaluate performance Accuracy, Precision, Recall, and F-measure. The suggested SVM-based method was 0.88 for date fruit classification. This demonstrates that the model's accuracy is higher than 88 percent of the time [20]. An automatic date fruit classification system has been suggested. Based on regional texture descriptors as well as shape and size parameters, the system has an accuracy of 98.1 percent. It is easy to implement and doesn't require any physical devices to measure size or form [21]. A methodology was developed to recognize various date types automatically utilizing outlier detection methods and Gaussian mixture models. The approach greatly outperformed several other approaches, with a high identification rate of 98.65 percent being attained [4].

Automatic fruit classification can increase efficiency and profit in the industry. It can help supermarkets and grocers identify different fruits and their condition from stock or containers, hence increasing production efficiency and profits. The research involved developing a lightweight deep-learning model without sacrificing classification [22]. Recent years have seen an increase in the use of image processing across several industries. The field of agricultural image processing and computer vision is another one that is expanding quickly. It is a crucial tool for post-harvest crop analysis as well as before and after-harvest analysis [23, 24]. The developer did an excellent job of classifying dates into several categories. A Gaussian mixture model was used to represent each type (GMM) The Calinski-Harabasz index was used for the ideal number of components for each GMM. This method can be used to study and research because it is extendable [25]. A system for date recognition using Deep Learning was created employing color, shape, and size feature extraction approaches. 500 images were employed, as well as 360 datasets. The best performance result of 97.2 percent at the fourth epoch was achieved by [6]. Using the CycleGAN-Generated Dataset, a Date Fruit Classification Improvement was made. ResNet152V2 and CNN models were used to train the model on the generated dataset. The CNN model had the second-highest classification performance, with 94.3 percent accuracy [26]. Date industries have had issues with date grading and sorting during harvesting. By automatically detecting and classifying an image, computer vision algorithms are utilized to decrease mankind's powers. The accuracy of a computer vision-based system was investigated using pre-selected date fruit samples from fields in Saudi Arabia [27, 28].

Pakistani date fruit export faces some serious challenges in local and international markets. Lack of awareness of packing, labeling, adaptation to modern refrigeration methodologies, and infrastructure for standardized classification and grading are some of the major issues faced by the industry. Pakistan date fruits export facing some serious challenges in local and international markets. Seasonal fruits, such as apples, bananas, mango, and date fruit are harvested from orchards or farms in batches. Categorizing dates into different classes is required and necessary for differentiating dates in terms of local quality and export quality [29]. This study aims to develop an intelligent system based on texture features analysis to accurately classify four date fruit varieties and acquire dates fruit datasets of four varieties (Aseel, Karbala, Muzawati, and Zahedi). The objectives of this study were: (i) To acquire a dates fruit dataset of four varieties (Aseel, Karbala, Muzawati, and Zahedi). (ii) To acquire the most discriminant texture features for achieving high classification accuracy. (iii) To develop an intelligent system based on texture features analysis to accurately classify four date fruits varieties.

2. Materials and Methods

As previously indicated, the classification of the several varieties of date palm fruits, including the Aseel, Karbala, Muzawati, and Zahedi dates, is shown in this study. The Muhammad Nawaz Sharif University of Agriculture Multan (MNS-UAM), Pakistan, is situated at 71° 27' 21'' (East) longitude and 30° 10' 51'' (North) latitude, and the full dataset process has been running there at an open environment [47]. According to the Pakistani time zone, a 13-megapixel (MP) images of date fruits grain was taken with an OPPO A54 cell phone between 11:00 (A.M.) and 2:00 (P.M.) [37] (Figure 1). Each Dates cultivar was assigned roughly 1200 fruit images as part of this investigation (Table 1). All images of dates were taken at 0.5 feet from the fruit.

Table 1. Information about the various varieties of date fruits and their image count.

S. No	Date Fruit	No. of Images
1	Aseel	300
2	Karbala	300
3	Muzawati	300
4	Zahedi	300

Figure 4 displays a graphical explanation of the process. Aseel, Karbala, Muzawati, and Zahedi are the four cultivars of date fruit that are shown, together with image acquisition and pre-processing, CNN architectures, and image classification.

In Figure 4 major steps involve Date fruits image dataset collection, images preprocessing which includes normalization, resizing, and RGB to grayscale conversion, classification into one of the four Dates fruits cultivars, CNN refers to convolutional neural networks, RGB refers to Red, Green, and Blue.

2.1. Image Acquisition and Pre-processing

Image when processing images for research purposes, pre-processing is a crucial component for any classification of the images. Pre-processing is required because of the various lightning circumstances, variations in dimensions, etc. [37]. With the assistance of horticultural experts, date fruits were procured from the Sabzi Mandi, a fruit and vegetable market, in Multan (Punjab, Pakistan), for the creation of a dataset. About 50 healthy fruits for each species of dates were used in the experiment. To minimize sun shadow effects, all photographs were taken with a still-mounted camera at a height of half a foot. Furthermore, on a clear, beautiful day at noon, all photographs were taken. Last but not least, a high-quality image dataset of 300 x 4 = 1200 colored images with a 2448 x 3264-pixel resolution.

To get a precise image, a white paper sheet was placed under the leaves before acquiring the leaf images and scanned at 72 dpi using a flatbed scanner. Furthermore, all the image datasets have been pre-processed by using free image convert and resize software. All the 1200 (300×4) colored image resolution was converted into (3264 × 2448) pixel size and 24-bit gray-scale level; it is also saved in JPEG format as shown in Figure 2.

Figure 1. RGB images of 4 Date fruit varieties.

Figure 2. Gray-level images of 4 Date fruit varieties.

Some pre-processing is also done on original images for the removal of unnecessary parts of the image. Aim to increase image quality and do better image analysis. The cropping technique was used to remove an extra part of the image. A sample of captured images with their cropped version is shown in Figure 3. To assure dataset quality, blurry and poor-quality images were removed from the original dataset.

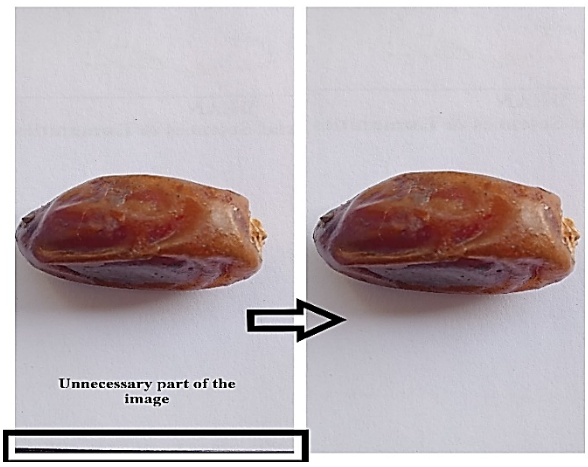

Figure 3. Sample of original image with their cropped images sample.

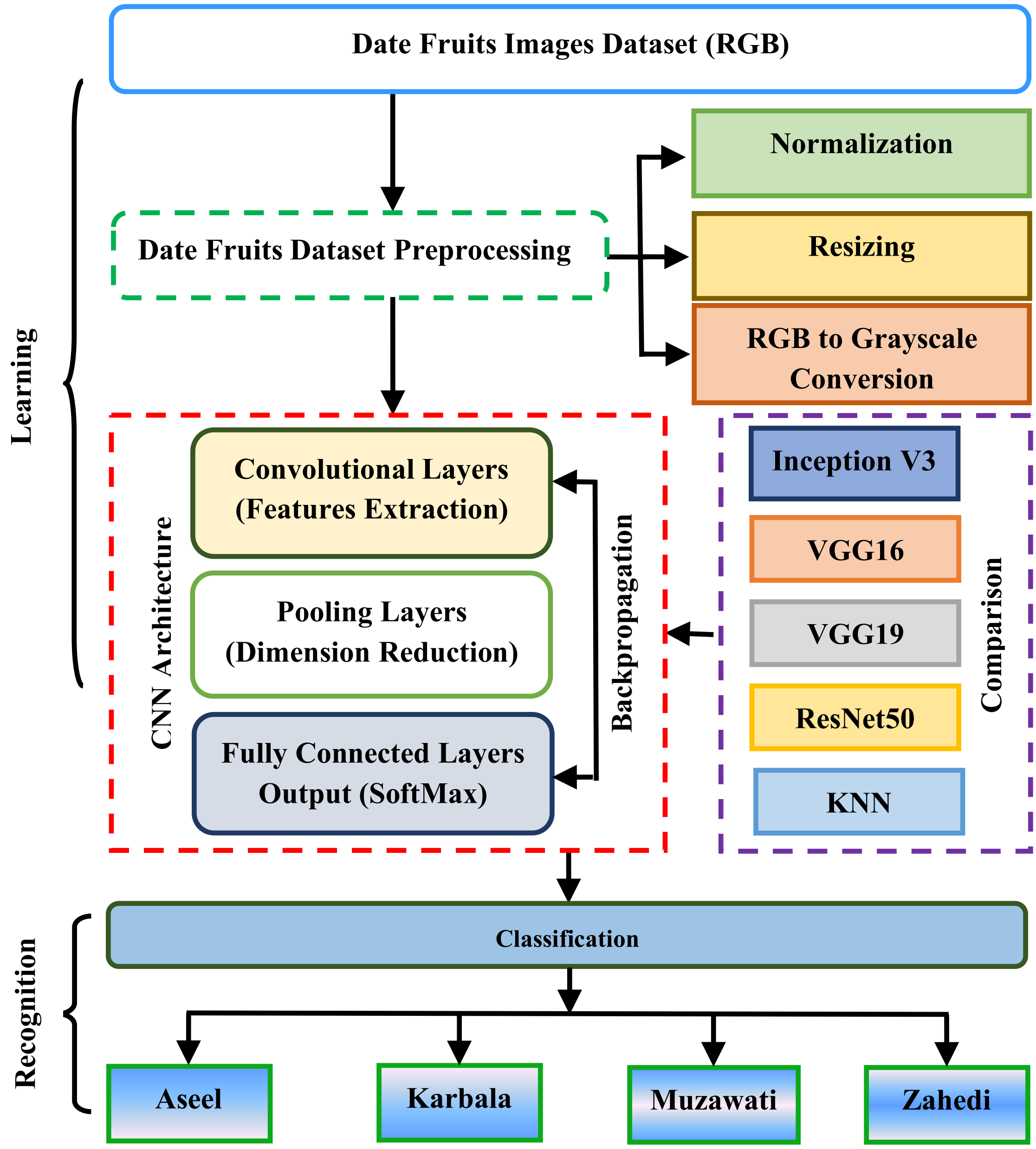

Figure 4. Graphical view of methodology.

2.2. Features Extraction

Feature extraction techniques are used after image pre-processing to extract features that can be used for image classification and recognition. Features illustrate where an image stands in terms of required storage, categorization effectiveness, and, naturally, time consumption [30]. The first layer in CNN is Convolution is the most important operation in image processing

It finds unique features while maintaining the pixels' relationship. Convolution is, in reality, an essential transformation procedure. To detect a specific feature, corresponding convolution kernels are employed. Feature extraction is a step in the dimensionality reduction procedure that divides and reduces a large amount of raw data into more manageable categories. Processing will be simpler as a result of this.

2.3. Classification

Figure 4 depicts the experimental setup for classifying dates as fruits. Some machine vision classifiers, including Convolutional Neural Networks (CNN), Inception V3, Visual Geometry Group (VGG 16 and 19), KNN, and Resnet50, were also tested on our proposed Dates fruit dataset to determine the effectiveness of our proposed model.

2.4. Texture Feature

One of the most important aspects of image data is texture, which is utilized to identify objects or regions of interest in an image. Textural images are those in which a precise pattern of texture distribution is reproduced sequentially throughout the image in image processing [31]. Texture analysis is the process of locating areas in an image based on the texture present in those areas. Because of the spatial variance in pixel intensities, texture analysis seeks to quantify the intuitive qualities denoted by adverbs like "rough," "smooth," "silky," and "bumpy" [32].

3. Convolutional Neural Network (CNN)

CNN (Convolutional Neural Network) is a well-known and well-established deep learning technique. CNN become more popular after AlexNet in 2012. AlexNet was based on CNN (5 convolutional layers plus 3 fully connected layers) [33]. CNN featured learning capability is very good for local and global features of image data [34]. The main advantage of CNN over other machine learning classifier is that it detects and extract key features automatically [35].

3.1. Convolutional layer

Convolution is a crucial transformation operation that performs image processing in the first layer of Convolution kernels are compact matrices that can be used to blur, sharpen, or detect image features in the original image. A kernel convolved with the input matrix horizontally (row-wise) and vertically to complete one convolution operation.

3.2. Pooling Layer

The following CNN layer's pooling function was used to decrease the inputs' dimension after the convolution processes. By minimizing computation, pooling also accelerates the model. The input (output of the preceding layer) was sent through the kernel in the pooling layer to capture the maximum value. Maximum pooling, which takes the highest value available from the pooling window, is the most popular pooling type. Convolution was carried out in conception v3 architectures utilizing stride 1 and the same padding on kernels with a 3 3 size [46].

3.3. Fully Connected Layer

Image classification was done in this layer. By retaining the important features in matrix form, the convolution and pooling procedures of the prior layers decreased the input's size. To categorize objects into labeled classes, a fully connected layer needs data in a one-dimension vector form.

CNN does the date cultivars categorization using Keras as the backend and TensorFlow libraries as the front end. The FitGenerator technique and ImageNet weight for transfer learning were used to train the classifier. This model requires input images in 299 299 formats [36].

The primary goal of the inception architecture is feature extraction at multiple levels. Together, these architecture convolutions (1 by 1), (3 by 2), and (5 by 5) are computed. Dropout and bottleneck layers were utilized to lessen the computational demand, together with a minimal number of neurons (effectively). For image rotation, translation, zoom, shearing, and flipping, Keras contains the class ImagedDataGenerator. Data augmentation was carried out to support the model's ability to memorize images with various attributes [32].

4. Results

In this study, four machine vision classifiers, namely CNN, InceptionV3, VGG16, and VGG19 were used, to compare how well four different variations of dates were classified using texture features. On the same dataset, KNN and ResNet50 were also tried and applied a 5-fold cross-validation procedure in the first set of studies. The outcomes were then contrasted with those of the classifiers described earlier. In terms of classifying the input images, it was found that CNN performed better than the other methods.

below provides more information on the CNN parameter settings that

Parameters	Parameters Values
No. of Layers	12
Learning Rate	0.001
Dropout	0.5
Validation Threshold	20
Epoch	10(min), 20(max)

employed in our experimental study.

Table 2. Values of the parameters of CNN used in our experimental

Parameters	Parameters Values
No. of Layers	12
Learning Rate	0.001
Dropout	0.5
Validation Threshold	20
Epoch	10(min), 20(max)

For maximum accuracy, the model was adjusted at different hyper parameter values. At five epochs and 64 batch sizes, the model classified Dates cultivars with a test accuracy of 97% and a test loss of 0.2. The dataset was divided into training and testing datasets, each including 80% and 20% of the total data set. By changing the epoch from 5 to 10, while maintaining the same batch size, the test accuracy was enhanced from 97 to 99 percent.

Epoch and batch size has been shown to significantly boost accuracy while reducing loss from 0.2 to 0.15. Additionally, accuracy started to deteriorate when the epoch was increased from 10 to 20 at a batch size of 64, resulting in a test accuracy loss of 0.19 and a test accuracy decrease to 97.12%.

To avoid the overfitting issue, epochs were not raised over 10 because it was noticed that doing so would cause the model to become over fit. The best results were obtained by testing the model at different hyper-parameter values, and they are shown in Table 3 for 10 epochs with 64 batch sizes. These results were 99.44 percent test accuracy and 0.15 test loss.

Table 3. Comparison of Results.

Model	Accuracy (%)	Loss	Val_Accuracy[1] (%)	Val_Loss[2] (%)	Eval_ Accuracy[3] (%)
CNN	99.44	0.145	98.83	0.159	99.26
InceptionV3	99.05	0.078	98.11	0.321	98.11
VGG16	98.43	0.151	97.92	0.578	94.55
Evaluation	98.10	0.141	95.99	0.471	95.10

([1]Validation Accuracy, [2]Validation Loss, [3]Evaluation Accuracy)

Figure 5 shows the overall training accuracy and validation of all the models which were trained on the date fruit dataset. From the figure, it can be concluded that ResNet50 has the lowest accuracy of 60.12% and 58.90% respectively. Whereas the results of KNN were better (88% and 87.1%) than ResNet50. Results of VGG19 slightly better than KNN with an accuracy of (98.1% and 95.99%). This occurred as a result of just training the newly added layers for the first 20 iterations before training only complete models for the remaining iterations. The proposed model's accuracy was 99.44% and 98.83% because it included customised heads in addition to other preprocessing methods. These preprocessing methods contributed to raising the prediction rate. The evaluation analysis of above mentioned models are shown in Figure 6.

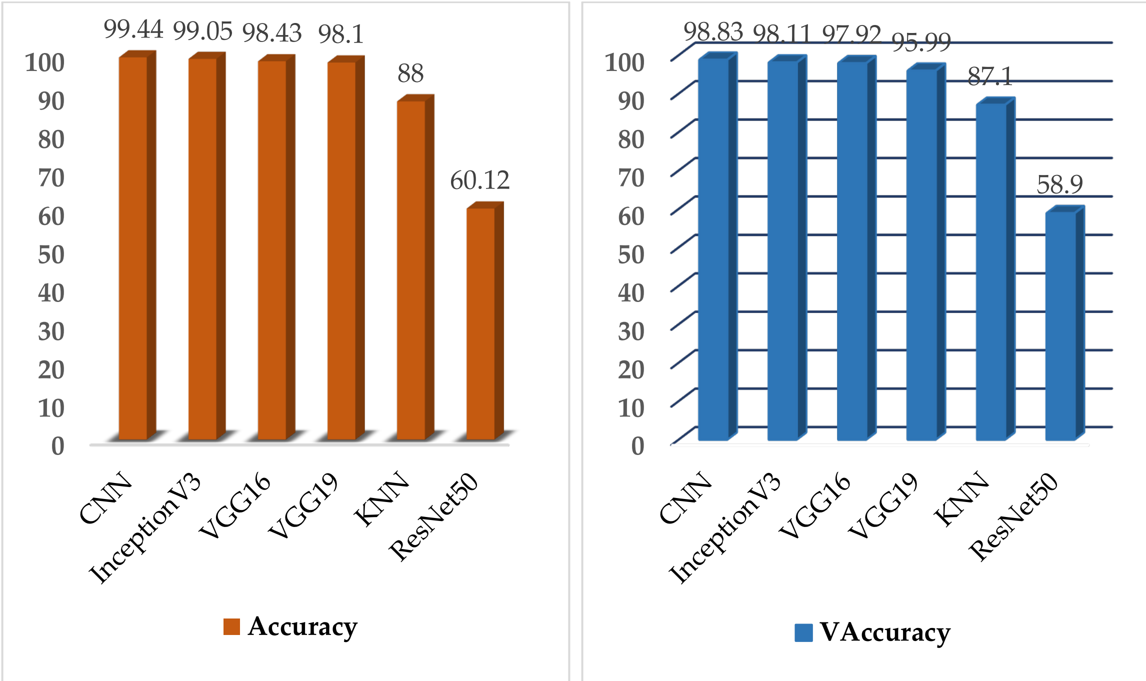

Figure 5. Training and validation Accuracy

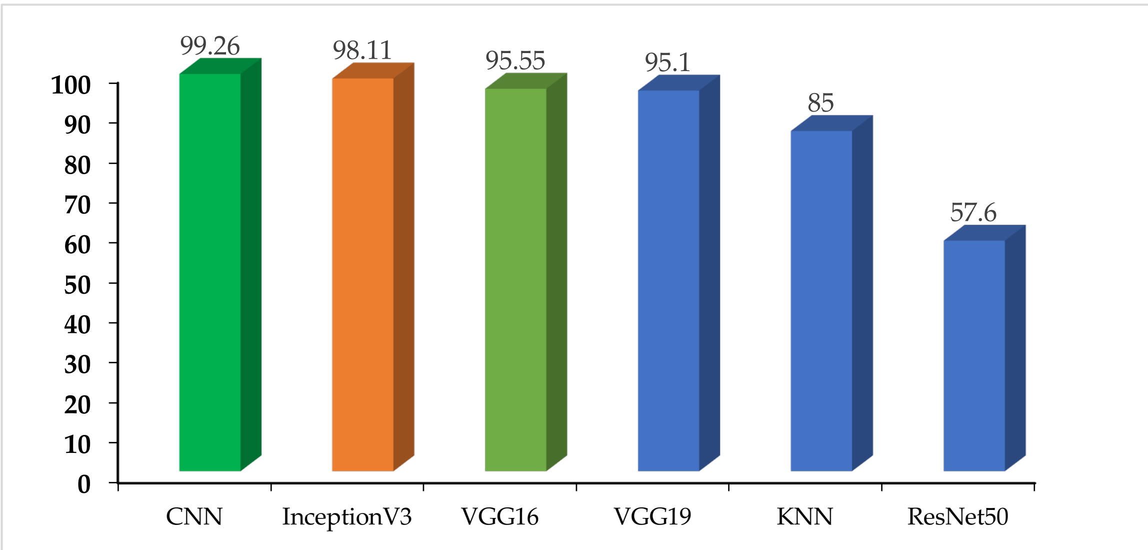

Figure 6. Evaluation Analysis.

5. Discussion

To effectively select the best varieties, cultivars, and dates varieties, date growers, and other end users can benefit from our suggested system's ability to distinguish dates varieties based on textural qualities. It may be used on huge datasets and is a reliable and effective method of reducing human error. There is a set resolution for each digital camera. Results may vary depending on how the camera is set up. Results for accuracy could fluctuate due to a modality difference.

This study employed fewer overall digital images than most others. The dataset should be sufficiently broad and condensed, with as many different types as possible, for general model testing and verification. Like to support others in the creation of a public sharing network for horticulture or agricultural datasets so that may deal with problems relating to plant research responsibly and professionally. And able to achieve some encouraging outcomes thanks to the following considerations.

1. Acquired the images of healthy Date Fruits.
2. To create a high-quality dataset of dates, pre-processing is done.
3. The CNN was found to be quite beneficial in obtaining high accuracy.

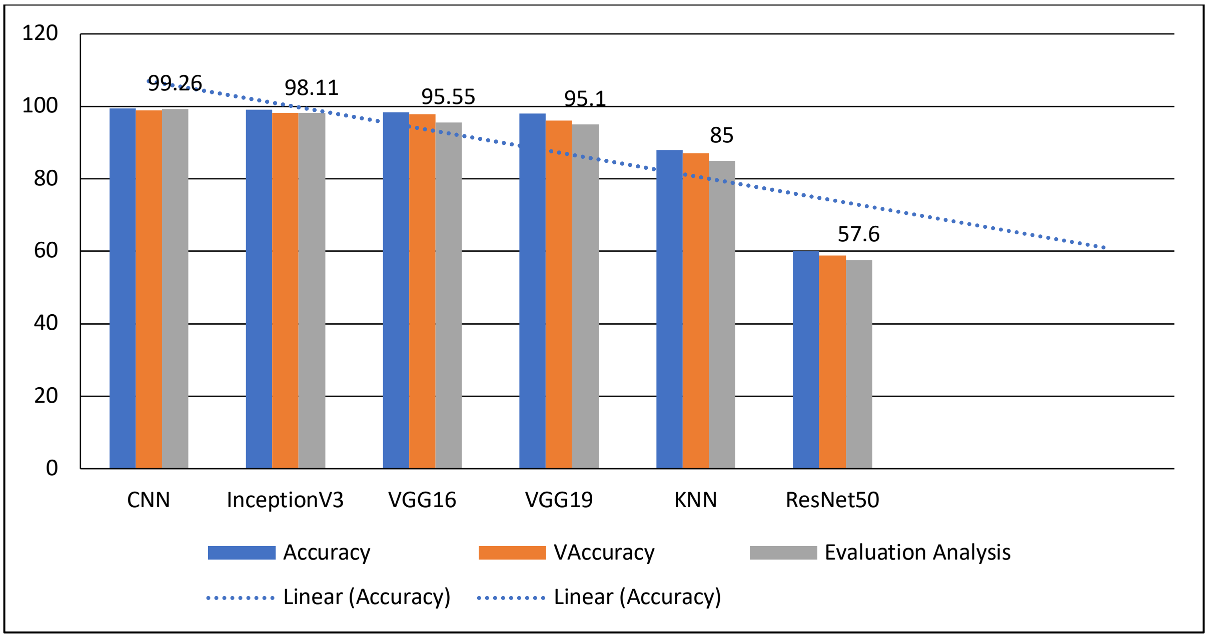

Figure 7. Overall Comparison Analysis

In terms of qualitative and quantitative features, the proposed work was compared with state-of-the-art methodologies as shown in (Figure 8). It is clear from Figure 8 that the majority of approaches used datasets that were self-collected. AI-based architecture is used in the majority of methods. The proposed method, which is based on the CNN architecture, fared much better on the gathered dataset. While processing, this architecture was faster and took up less space than the other architectures, performing equally as well. The fact that the dataset was gathered using a smartphone means that this architecture is best suited for it.

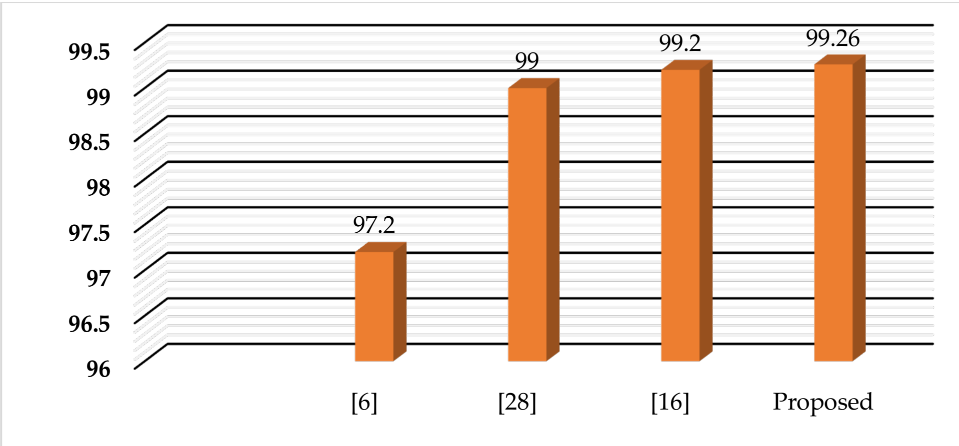

Figure 8. Comparisons with previous studies

6. Conclusions

The goal of this effort is to categorize popular four different date varieties (Aseel, Karbala, Muzawati, and Zahedi) of Pakistan using a dataset of date fruits. Date fruit are 3rd most important crop of Pakistan. Four machine learning classifiers—CNN, Inception V3, VGG16, and VGG19—were able to use this dataset successfully for evaluation. For evaluation purposes, a date fruit image dataset of 1200 images have developed for experiments. A new set of metrics was used to assess the dataset and categorize the date fruits. Into the proposed model, preprocessing techniques have been employed to improve the accuracy rate such as changing learning rate, batch size, and dropout etc. For maximum accuracy, the model was adjusted at different hyper parameter values. The results from all the classifiers were good, but CNN stood out since it achieved 99.26% accuracy on the four different varieties of date fruits. According to the achieved accuracy rate, the suggested technique is robust and appropriate for real-time applications. In the future, a new property of the same dataset would be added to reflect the changing of texture feature values with lighting conditions. This study's classification of date fruits could also contribute to the development of a simple, less-cost method for diagnosing date diseases that do not require sophisticated systems or expensive machinery. A comparison of four alternative architecture variants led to the identification of the best test architecture, and potential ablation research could further explore the options.

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