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Data Enhancement for Date Fruit Classification Using DCGAN **

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ABSTRACT

Date fruits are considered essential food and the most important agricultural crop in Saudi Arabia. Where Saudi Arabia produces many types of dates per year. Collecting large data for date fruits is a difficult task and consumed time, besides some of the data types are seasonal. Wherein the convolutional neural networks (CNN) model needs large datasets to achieve high classification accuracy and avoid the overfitting problem. In this paper, an augmented date fruits dataset was developed using deep convolutional generative adversarial networks techniques (DCGAN). The dataset contains 600 images for three varieties of dates (Sukkari, Suggai, and Ajwa). The performance of DCGAN was evaluated using Keras and MobileNet models. An extensive simulation shows the classification using DCGAN with the MobileNet model achieved 88% of accuracy. Whilst 44% for the Keras. Besides, MobileNet achieved better classification in the original dataset.

1 Introduction

Date fruits are essential for human consumption. Due to the fact that dates contain critical nutrients and have several health benefits, they are widely consumed. In addition, date fruits are thought to be an effective preventative against a variety of ailments, including heart disease and cancer [1]. In addition to its nutritional significance, the date fruit is an important agricultural product in nations throughout the Middle East and Northern Africa, and it plays a significant part in the economies of these countries. In particular, Saudi Arabia, which is considered to be the world's third-largest producer of date fruits in 2020 and the world's second-largest producer of date fruits in 2020, where the production of date fruits increased from 811,799 tons in 2000 to 1,884,846 tons in 2020 [2], as illustrated in Figure 1 and Figure 2.

Since dates accounted for 11.7 percent of Saudi exports in 2018, this is a significant figure. It produces almost 400 different types of dates, including Khalas, Sukkari, and Berhi, among others [3]. The National Center for Date Palm in Saudi Arabia [4] developed a questionnaire to indicate which types of date fruits were the most popular in the country. According to the results of the study, which included 8518 respondents, the most popular types of dates were Sukkari, which received 69.5 percent of the vote, followed by Khalas, which received 48.4 percent, and Rutab, which received 11.1 percent. Last but not

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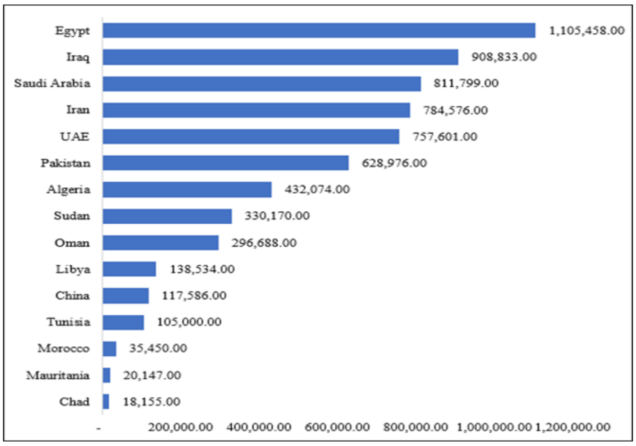

Figure 1. The top 15 largest dates producer countries in 2000

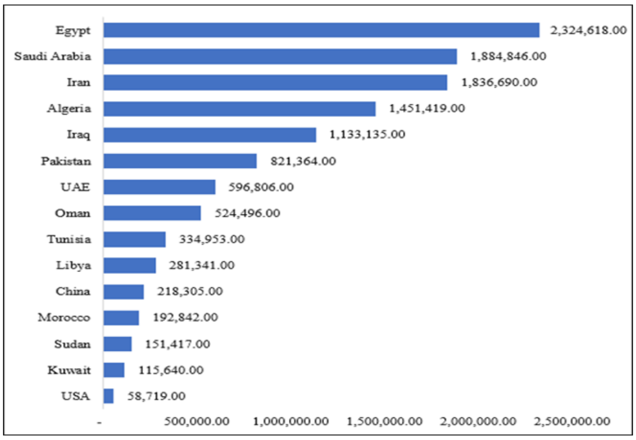

Figure 2. The top 15 largest dates producer countries in 2020

least, Suggai with 11 percent [5].

In a recent study, we demonstrated that when we employed Convolutional Neural Network (CNN) to identify photos of date fruits, we achieved a good degree of accuracy. A bigger amount of training data is required for the CNN model to achieve improved outcomes in the categorization of date fruit. The collection of vast amounts of data in the agricultural field, particularly for date fruits, is a time-consuming and resource-intensive task that necessitates more resources and time. As previously stated, there is no public dataset on date fruits, which is a significant limitation. All of the prior research developed their datasets and did not make them available to the public, save for one study at H. Altaheri *et al.* [6]. give a dataset comprising five different varieties of dates; moreover, the collection also comprises photographs of dates taken in an orchard environment at various stages of development.

Data augmentation approaches, which are being introduced, can address these concerns. Fundamental picture manipulation and advanced image modification techniques were used to generate new data from existing training data, eliminating the requirement to acquire new data [7].

The purpose of this paper is to supplement date fruit datasets that we have developed using Deep Convolutional Generative Adversarial Networks techniques to improve their accuracy. The problem of a restricted number of images in our datasets and an imbalanced dataset must be addressed to be resolved. The dataset comprises three different types of dates, which are as follows: (Sukkari, Barhi, and Ajwa). To categorize three different varieties of date fruits and evaluate their performance, state-of-the-art models using approaches such as the Keras Model and the MobileNet model are employed.

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It was determined how well the data augmentation strategies performed by examining the performance of state-of-the-art transfer learning algorithms such as VGG16, ResNet, and InceptionV3. An extended simulation demonstrates that the augmented dataset created using GAN and NST algorithms achieves greater accuracy than the original dataset created using a basic image manipulation-based augmented dataset (as opposed to the original dataset). Furthermore, when Deep learning, color, and position augmentation datasets are combined, the classification performance is superior to that of all other datasets.

The remaining section of this paper is as follows. Section 2 describes the related work-related. Section 3 present the methodology and materials, where explain the dataset and the models. Section 4 reports the experimental results and discussion. Finally, we conclude in Section 5.

2 Related Work

Specifically, the goal of this part is to provide examples of the many date augmentation approaches that have been employed in prior research and applied to plant and leaf datasets. Which have characteristics that are similar to the date fruit dataset. Present studies on date fruits, as well as previous research.

According to R. Gandhi and colleagues [8], they suggested a system that automatically classified types of plants and their diseases based on the leaf, to assist Indian farmers. Using the PlantVillage dataset, the scientists were able to collect more than 56,000 photos (from 38 classes and 19 crops). The photographs in this collection depict crops that are farmed locally, as well as the diseases that affect them. When the authors needed to supplement the restricted quantity of datasets, they employed the Deep Convolutional Generative Adversarial Networks (DCGAN) algorithm. They then used the MobileNet model and the Inception-v3 model for classification. As a result, the model's accuracy for Inception-v3 and MobileNet was 88.6 percent and 92 percent, respectively, according to the results. In a similar vein, the authors M. Zhang *et al.* [9] employed DCGAN to supplement the citrus canker photos to address the issue of a limited number of images being accessible at the time. 800 photos have been modified six times and then fed into the generative model to produce the final result. Using DCGAN with custom mute layers, they trained the model over 2,000 epochs, and the results were quite promising. Then, depending on the diagnosis of human experts, divide a dataset into two categories: positive and negative, respectively. With 100 epochs of training, the AlexNet classifier was able to attain an accuracy of 93.7 percent on the classify task.

Using the Gambung Clone dataset, which consists of two different types of Gambung tea clones and a total of 1297 leaf images, E. Suryawati and colleagues [10] suggested an unsupervised feature learning architecture derived from DCGAN for automatic identification of Gambung tea clones. As a feature extractor, the proposed feature learning architecture appends an encoder to the DCGAN network, allowing it to distinguish between different Gambung tea clones. The model's accuracy was 91.74 percent, and the model's loss was the smallest at 0.32 percent.

For example, researchers J. Arun Pandian and colleagues [7] used picture augmentation techniques, as well as deep learning-based image augmentation approaches, to overcome the problem of a lack of data in agricultural fields. Particularly difficult responsibilities were the identification and diagnosis of plant leaf disease, which were both time-consuming and expensive. Specifically, the plant leaf disease dataset was employed, which contains 38 distinct healthy and sick classes, as well as 54305 photos of plant leaves in total. In order to validate the performance of data augmentation strategies, state-of-the-art transfer learning techniques such as VGG16, ResNet, and InceptionV3 were used. The authors conducted an experiment in which they employed fundamental image manipulation techniques such as image flipping, cropping, rotation, and so on, and generated a total of 32073 images. Whereas DCGAN and Wasserstein GAN (WGAN) augmentation approach yield 32073 enhanced images, and the Neural Style Transfer (NST) augmentation techniques generate 6038 images, DCGAN and WGAN augmentation techniques generate 32073 augmented images. The best-performing model was InceptionV3, which achieved the highest accuracy across all datasets compared to other models, with accuracy rates of 89.9 percent, 90 percent, and 93 percent on basic image augmentation, DCGAN, WGAN, and NST, respectively, compared to other models.

There have been a plethora of studies undertaken on the date fruit in general. Although there have been some studies on date fruit categorization, the number of studies using CNN as a classifier has been minimal, particularly in recent years. Furthermore, only a few datasets are made publicly available.

For the classification of date fruits, H. Altaheri and colleagues [6] suggested a deep learning-based machine vision framework. This dataset, which contains 8072 date photos taken in an orchard environment, was developed by the students. The dataset contains five different varieties of dates (Naboot Saif, Khalas, Barhi, Meneifi, and Sullaj) that are at various stages of maturity (Naboot Saif, Khalas, Meneifi, and Sullaj). This dataset is freely available to the public. The authors used two CNN architectures, namely AlexNet and VGGNet, in their research. As a consequence, the proposed model attained an accuracy of 99.01 percent, 97.25 percent, and 98.59 percent, respectively, in three different tests.

As well as the authors Faisal *et al.* [3] proposed a system to classify date fruits in orchards based on maturity for an intelligent harvesting decision system (IHDS). The proposed system can detect seven maturity stages of dates in an orchard which are (Immature stage 1, Immature stage 2, Pre-Khalal, Khalal, Khalal with Rutab, Pre-Tamar, and Tamar). They used dataset from Altaheri *et al.* [6]. They used three architectures of CNN which are VGG-19, Inception-v3, and NASNet. Experimentally, the maximum performance metrics of the proposed IHDS were 99.4%.

On the other hand, Nasiri *et al.* [11], used CNN to classify the (Shahani dates), based on the maturity stages (Khlal, Rutab, and Tamar). They created their dataset and collected more than 1300 date images But the dataset is not available. The CNN model was constructed from the VGG-16 model with a fine-tuning network. As result, the average per class of classification accuracy ranged from 96% up to 99%. Whilst Magsi *et al.* [6], proposed deep learning with computer vision techniques model to recognize date fruits in Pakistan. After the pre-processing and features extraction, they used CNN to classify three

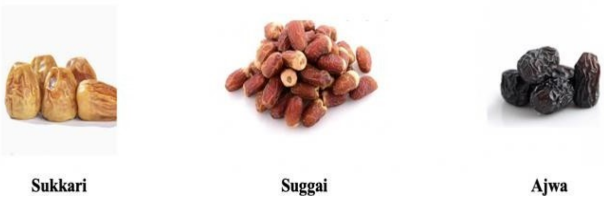

Figure 3. Sample dates from the datasets

Table 1. Description of number of images in dataset

Type of class	Train set (80%)	Test set (20%)	Total (100%)
Sukkari	169	50	219
Suggai	165	53	209
Ajwa	156	44	200
Total	490	147	628

types of date fruits (Aseel, Karbalain, and Kupro) based on the features (Color, Shape, and Size). They created their dataset which consists of 500 images and is privately available. However, the model achieved 97% accuracy. Similarly, Dina *et al.* in [12] used Deep Convolutional Generative Adversarial Networks (DC-GAN) and CycleGAN. This augmentation is required to address the lack of images in our datasets and to create a balanced dataset. The CycleGAN-generated dataset had the highest classification performance with 96.8% accuracy when using the ResNet152V2 model, followed by the CNN model with 94.3 percent accuracy.

3 Materials and Methods

This section presents the description of date datasets. Followed by the details of the DCGAN augmentation techniques. Subsequently, Offer the structure of CNN and Mobilenet models.

3.1 Datasets

To build a robust vision system in deep learning a rich image of the dataset must be created. Due to the lack of a publicly available dataset. We created a dataset consisting of 628 images of three varieties of date fruit namely Sukkari, Suggai, and Ajwa. We collected images manually from an online website and by using smartphones and stored them in .jpg format. All the images of varieties of dates are in the Maturity stage (Tamar stage). However, each variety of date is different in features such as shape, color, texture, and size from others as in Figure 3.

The dataset was labeled into three type classes, Table 1 shows the distribution of the dataset images between these classes. Where the images are different in size and background. For data dividing, we divided the dataset into training and testing sets (80% of the images for the training set and 20% for the testing set). Besides, showed the number of images for the training and testing set.

3.2 Data Augmentation and Deep Convolutional Generative Adversarial Network (DCGAN)

Deep learning networks include an excessive number of parameters; as a result, the training model requires a huge amount of data to learn these parameters. The model training will be over-fitting if this is not the case. Data Augmentation is a viable approach for increasing the size of the training dataset without the need to collect additional data sources. Utilizing both fundamental picture manipulation and advanced image transformation algorithms, it generates fresh data from the previously collected training data. The Generative Adversarial Network (GAN) is the most often used advanced approach (GAN). To overcome the limitations of datasets such as the scarcity of datasets and the imbalance of datasets, approaches such as Data Augmentation are employed.

The Generative Adversarial Network (GAN) is a deep learning network that also serves as a generative model for adversaries. GAN is composed of two neural networks, which are referred to as the Generator and the Discriminator. GAN generates new data from existing data, to generate pictures that are similar to real data without the user having to view it. Discriminator, on the other hand, attempts to distinguish between artificially generated data and real data. The training procedure will come to an end when the discriminator accuracy becomes so low that the generated images appear to be very realistic in appearance.

Specifically, Deep Convolutional Generative Adversarial Network (DCGAN) is a form of adversarial network that constructs the generator and discriminator using a convolutional neural network (CNN). In contrast to supervised learning, DCGAN is a system that bridges the gap between successful CNN training and unsupervised learning. GAN performance is improved by using DCGAN, as opposed to regular GAN. For this reason [13], it is the classification method most widely employed in agriculture and medical imagery. Instead of the max-pooling layers used in GAN architecture, stride convolutions on the discriminator and fractional-strided convolutions on the generator were employed in the DCGAN architecture. Furthermore, batch normalization was used on both the discriminator and the generator, ReLU activation was used in the generator for all layers except at the output, employing tanh was used in the discriminator for all layers, and LeakyReLU activation was used in the discriminator for all layers.

3.3 Convolutional Neural Network (CNN)

CNN is a mathematical construct that is made up of three sorts of layers: convolutional, pooling, and fully connected layers. Convolutional layers are the most basic type of layer while pooling layers are the most complex. In this algorithm, the convolution and pooling layers extract picture features, and a fully connected layer translates these retrieved features into the final output, which is classification. As illustrated in Figure 4, the conventional CNN design consists of one or more stacks of numerous convolutions and pooling layers, followed by one or more fully linked layers, as shown in Figure 4. The output of one layer feeds the output of the subsequent layer, resulting in a hierarchical increase in the complexity of the retrieved features [14].

3.3.1 Convolution Layer

Convolution layers are composed of a combination of linear and nonlinear operations, such as the convolution operation and the activation function, that are used to extract features from a data set. A convolution operation is a form of linear operation in which a tiny array of parameters known as the kernel is applied to the input image to extract features from it. The convolutional technique employs many kernels to generate various feature maps, with each kernel extracting a distinct set of features from the final feature map. The result of the linear operation is processed through a nonlinear activation function to construct the activation maps, with only the features that have been activated being sent on to the next layer. Most widely used is the rectified linear unit (ReLU), which is easily calculated using Equation 1. If any negative value x is received, the function returns 0, but if any positive value x is received, the function returns 1 [14, 15].

$$f(x) = max(0, x) \begin{Bmatrix} 0 \ \ if x < 0 \\ x \ \ if x \geq 0 \end{Bmatrix} \quad (1)$$

3.3.2 Pooling Layer

A pooling layer reduces the dimension of the feature maps to reduce the number of learnable parameters that can be learned from the feature maps [14, 15]. The most frequent sort of pooling operation is max pooling, which aggregates patches from the input feature maps, obtains the largest value in every patch, and discards the remaining values. Mathematically represented by Equation 2:

$$f_{max} = max_{nxm}(A_{nxm}) \quad (2)$$

3.3.3 Fully Connected Layer

The feature maps formed by the final convolution or pooling layer are flattened to make them easier to read. In other words, the mean has been transformed into a numerical one-dimensional array and linked to one or more completely connected layers. The completely connected layer, also known as the dense layer, is characterized by the fact that each input is coupled to each output by weights. The final fully connected layer has an output node count that is equal to the number of classification classes plus the number of SoftMax activation functions that have been applied. SoftMax is the most known function used in the classification tasks and given by the equation Equation 3 where n neurons for n classes, pi is the prediction probability value, ai is the softmax input for class I and i, $j \in \{1, 2, ..., n\}$

$$pi = \frac{\exp(at)}{\sum_{j=1}^{n} exp(ai)} \quad (3)$$

The Deep learning CNN model is most likely the most efficient method of automated classification in agriculture and food production [11, 14]. This study proposes a classification model using CNN to automatically classify dates based on their types i.e. Sukkri, Sagei, and Ajwa. The model architecture is outlined in Table 2. We used Python 3.6 using Keras library to build and train the CNN model.

3.4 MobileNet Architecture

The MobileNet model is one of the effective CNN architectures, which can apply to a variety of tasks [16, 17]. MobileNet model architecture primarily focuses on building a small network with a low latency model whereas other architectures focus on building a small size network but do not consider the speed. MobileNet architecture outperforms the VGGNet (1st Runner Up of ILSVRC 2014) and GoogLeNet (Winner of ILSVRC 2014) on ImageNet competition with the multi-adds and parameters being much fewer [16] as in Table 3.

Because of the compact nature of the MobileNet architectural concept, which is based on depth-wise separable convolution, it allows for easier computing while maintaining excellent performance. The MobileNet algorithm made use of two global hyperpa-

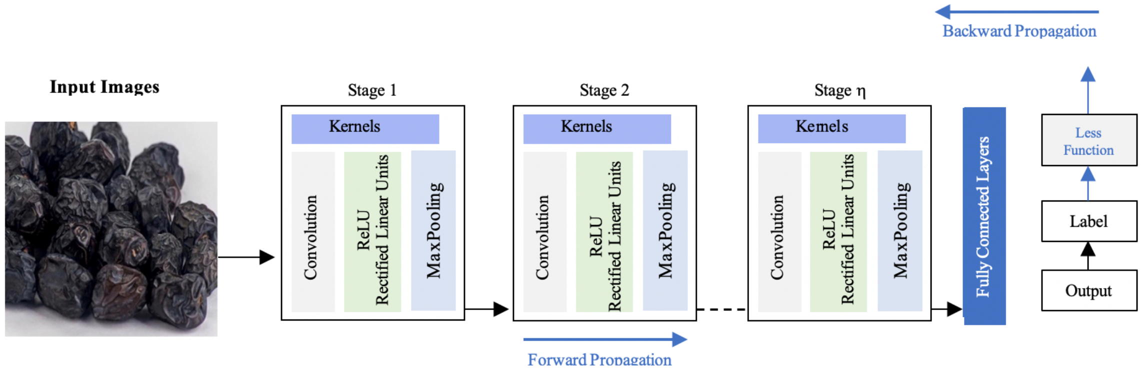

Figure 4. The proposed CNN model architecture

Table 2. The summary model of the proposed CNN architecture

Layer (type)	Output Shape	TParam#
conv2d_6 (Conv2D)	(None, 98, 98, 200)	5600
conv2d_7 (Conv2D)	(None, 96, 96, 150)	270150
max_pooling2d_3 (MaxPooling2)	(None, 24, 24, 150)	0
conv2d_8 (Conv2D)	(None, 22, 22, 120)	162120
conv2d_9 (Conv2D)	(None, 20, 20, 80)	86480
conv2d_10 (Conv2D)	(None, 18, 18, 50)	36050
max_pooling2d_4 (MaxPooling2)	(None, 4, 4, 50)	0
flatten_2 (Flatten)	(None, 800)	0
dense_5 (Dense)	(None, 120)	96120
dense_6 (Dense)	(None, 100)	12100
dense_7 (Dense)	(None, 50)	5050
dropout_2 (Dropout)	(None, 50)	0
dense_8 (Dense)	(None, 3)	153
Total params: 673,823		
Trainable params: 673,823		
Non-trainable params: 0		

Table 3. Comparison MobileNet model with popular models on ImageNet dataset

Model	ImageNet Accuracy	Million Adds	Mult-Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
GoogleNet	69.8%	53	209
VGG 16	156	1550	6.8
Total	71.5%	15300	138

Table 4. The summary model of the proposed MobileNet architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 225 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw/ s2	$3 \times 3 \times 643$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw/ s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$56 \times 56 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
5X Conv dw/ s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

rameters to achieve a good balance between performance and accuracy. Except for the first layer, which is a fully linked layer, the MobileNet structure is constructed using depth-wise separable convolutions. The MobileNet architecture is comprised of 28 layers, which are represented in Table 3, and these layers define the MobileNet architecture [16, 18], Batch normalization and ReLU non-linearity are applied to each of the layers, except for the last layer. The final layer is fully connected, does not exhibit non-linearity, and feeds into a SoftMax layer for classification before being removed. After each convolutional layer, the 3 * 3 depth-wise separable convolutions with depth-wise convolution and 1 1 point-wise convolution layers are shown, followed by batch normalization and ReLU after each convolutional layer in Figure 5 Downsampling is done by the first layer, and in the depth-wise convolutions, it is handled by stridden convolution. A final pooling layer is used to reduce the spatial resolution to 1 before the fully connected layer [16, 18].

4 Results and Discussion

As mentioned before the main issues of our dataset are the limited number of date fruit images and imbalance through each data type in the dataset. Moreover, the date fruit classification becomes a challenge due to the similarities among date types [19]. In order to overcome these issues and based on the previous research, we found that DCGAN is a suitable solution. It will augment the limited number of date fruit images, generate high-resolution images, and increase the accuracy as well. Besides, none of the previous research used DCGAN on-date fruit datasets.

The experiment started with date image augmentations. We use the DCGAN augmentation method that can be effectively used in supervised and unsupervised learning [20, 21]. First, to augment the date fruit images we trained the DCGAN in our date fruit dataset by using the Colab platform. We start with a few numbers of iterations increased lately to 2000 iterations. After each iteration, the model learns and generates high-resolution images. We apply DCGAN for each date type separately which are Sukkari, Suggai, and Ajwa, and add the generated images to the dataset. Additionally, after we apply the DCGAN augmentation method on the same dataset by 2000 iterations we see the results have been improved. Figure 6 presents a combination of some of the generated images of Sukkari date types by the DCGAN augmentation method.

Secondly, we build deep learning CNN model by using the Keras library to classify the date fruit dataset before and after applying the DCGAN. Keras is a library that provides highly powerful and abstract building blocks to build deep learning networks [22]. The power of Keras is the combination of TensorFlow and Theano libraries so we use it in this CNN model [23]. To use such a library, we create and define our model, define the loss function, and feed the model. The architecture of the implemented CNN is composed of five convolutional layers with 3×3 kernels and two 4×4 max-pooling layers. For every convolutional layer, we applied the activation function (ReLU). After the second max-pooling layer, flatten layer was applied to flatten the output and then crossed through three dense layers or fully connected layers.

Afterward, the dropout layer was added for regularization to reduce the overfitting risk in the training. The dropout rate was set to 50%. Lastly, the output of the last dropout layer was passed through a fully connected layer that has three neurons and applied the SoftMax activation function. Every neuron represents a classification class and the SoftMax function predicts the tested image belongs to which class. We

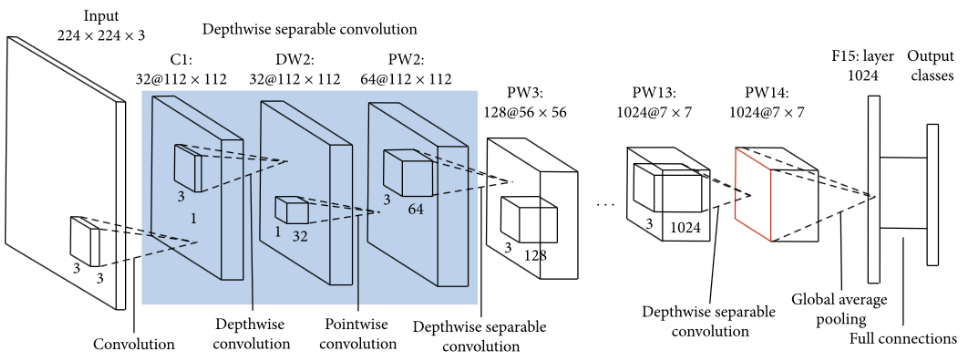

Figure 5. The Mobilenet proposed architecture [19]

Figure 6. Generated images of Sukkari dates type

train our model on a sample of dates fruit dataset containing 156 images of Ajwa dates type, 165 images of Suggai, and 169 images of Sukkari dates type. After we train our model, we use the augmented dataset to test the model performance and measure its accuracy. We use this model as well to compare the first model results and MobileNet results and decide the best classifier for our dataset.

Lastly, on the other side, we train another model by our dates fruit dataset to notify the improvements of the results if any. The reasons behind choosing such a model are the efficiency of latency and high server performance [24]. We start training the model using a small number of epochs increased lately. We compare the results after each iteration and notify the improvements of such a model. Then we use the same model for the dates fruit dataset after applying DCGAN on the images to evaluate the improvement of our dataset. Our source code is available at https://github.com/ParkandPay1/Data_Enhancement_for_Date_Fruit_Classification_Using_DCGAN_Project.

4.1 Performance Evaluation of Classifier Models Before DCGAN

The obtained results from training the classifier models on the original dataset are explained in this subsection. As we run the CNN model on the dates fruit dataset and by applying 20 iterations, we achieve 62% of accuracy and 0.55 test loss. For the second model, which is MobileNet, we reach 81% of accuracy after

Table 5. The accuracy of Keras and MobileNet models

Model	Accuracy before DCGAN	Accuracy after DCGAN
Keras	62%	44%
MobileNet	83%	88%

20 iterations and 2.27 test loss. After that, we try to increase the iterations by 5 iterations and reach 0.83 accuracies of MobileNet. By comparing the results of such models, we found that MobileNet is better than Keras-based CNN in the accuracy difference. In such an experiment, accuracy plays an important metric to verify the effectiveness of the proposed models as it has been used by previous researches [8, 10, 25, 26].

4.2 Performance Evaluation of Classifier Models After DCGAN

For the Keras-based CNN model, the accuracy differentiates by 18% decreasing and reaches 44% of accuracy. Moreover, the CNN model did over-fitting which is considered a weak point and drawback of the model to do a good performance. The model "is said to overfit to its training data when its performance on unseen test data diverges from the performance observed during training" [24]. On the other side, the MobileNet model achieves 88% accuracy after 25 iterations. Based on the results and after comparing the proposed models, we find that MobileNet is better than the Keras model even before or after data augmentation. More to that, we find the DCGAN augmentation method is suitable for our datasets because it generates high-resolution images and increases the dates fruit dataset.Table 5 presents the obtained results for the proposed models.

5 Conclusion and Future Work

Date fruits classification based on their types faced many limitations due to the lack of publicly available datasets. Additionally, deep learning classification models require a large number of training data to learn their all parameters. For this reason, Data Augmentation is used to overcome the limitations and avoid training overfitting. Therefore, in this study, we used DCGAN to maximize the date dataset that consists of three types Sukkari, Suggai, and Ajwa. We used two classification models i.e., Keras-based CNN and MobileNet twice, before and after applying DCGAN to notify any performance improvements. The obtained results of the first classifier, the CNN classifier, was 62% and after DCGAN decreased to 44%. While MobileNet increased from 83% to 88%. To conclude, the MobileNet is better than Keras-based CNN even before or after data augmentation. As well DCGAN is the most used in agriculture and food classification.

In future work, we would like to extend the data augmentation process by using other augmentation techniques besides DCGAN. Moreover, adding more date types in the dataset to improve the performance of our unsupervised learning models

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