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# DeepPalm: Deep Learning Classification Model for Date Palm Varieties

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**Abstract:** Dates being UAE's national fruit, as well as KSA and UAE's national tree hold great importance. Dates are in high demand because of their distinctive flavor, health benefits, and religious significance. Dates come in a variety of flavors, textures, sizes, and shapes. Pakistan produces around 300 different date kinds, of which Dhakki, Aseel, and Begam Jangi are the most common. The choice and quality of this fruit in the local market are mostly determined by human visual perception. The analysis of the quality and selecting the wrong variety concerning demand leads to a loss of product quality and dishonor in the case of export. Intelligent machines have served humanity in these last decades in different aspects of life. Image processing technology has been used extensively in the medical field as well as in agriculture. Identification and classification represent a major challenge for machine learning to achieve almost human recognition levels. This research aims to develop an intelligent method, which would be able to identify and classify date types according to form, size, and color characteristics using machine learning and deep learning. As a first step, the pre-processing technique will be adopted to improve the quality of datasets. The processed images will then be categorized with an appropriate classifier. The proposed system is intended to classify different kinds of dates. To effectively learn and distinguish the types of date fruits with high accuracy, a convolutional neural network (CNN) was constructed and trained from scratch, with nearly 9200 date fruit images which include 1500 images of each of six varieties. The improved model's classification accuracy was 98%. These findings proved the CNN model's ability to recognize types from dates with high accuracy so that it can be used at the industrial level.

**Keywords:** Machine Learning; CNN; Date Classification; Deep Learning.

## 1. Introduction

The agricultural industry works around every day to meet the population's requirements for food. Furthermore, agriculture contributes significantly to a nation's economic development. Due to their nutritional worth and potential for treating and preventing a wide range of ailments, dates are a fruit that is high in dietary fiber and has a global economic value. For decades, humankind has tried to recompose its technological equivalent when it comes to intelligence, feelings, and behavior [1]. Rich in nutrients, date fruit is an excellent calcium, potassium, vitamin C, and iron source. Date trees are grown all over the world, but in the Middle East and Saudi Arabia, in particular, they are regarded as a prominent fruit kind. Dates also known as the "tree of divine providence", come in a variety of flavors, textures, sizes, and shapes, and can be distinguished by their taste, texture, size, and form [2]. Only Pakistan produces almost 300 distinct varieties of dates which is the 7$^{th}$ largest date-producing country. Date Fruit has a lot of varieties and is very difficult to identify as most of them may have the same color, shape, size, or texture [3]. Dates identification is the application of Fruit Classification. Identifying dates involves creating a system that can differentiate and categorize images or samples of dates from other fruits or things. It is an extensively sparkling space of research and received significant attention. Extensive work has been done in the past for classification, grading, detecting, and quantifying the fruits. A lot of work previously done is on grading and harvesting [4]. Work on disease detection in fruits and quantification is also extensively available. The dataset used in this method consists of 2358 images of the four major and well-known date palm species, Barhi, Sukkari, Ikhlas, and Saqi. The author also used techniques for data augmentation to increase the size and diversity of our dataset. The new dataset was then used to train and refine the proposed model, which was given the title DPXception (Date Palm Xception). Since the suggested DPXception model simply extracts features from the first 100 layers of the Xception model, it is both lighter and more efficient than the initially created Xception model [5]. Significant advancements in artificial intelligence, machine learning, and computer-based image analysis have simplified the process of extracting quality parameters from agricultural items, fruits, and vegetables based on their shape [6]. Eight different varieties of date fruit were created as a dataset, which was used to train the proposed model in this work. The proposed model has included many preprocessing techniques, such as picture augmentation, decaying learning rate, model checkpointing, and hybrid weight modification, in order to increase the accuracy rate. Based on the MobileNetV2 architecture, the results show that the proposed model has 99% accuracy. The proposed model has also been compared to other models that are in use at the moment, such as ResNet, AlexNet, InceptionV3, MobileNetV2, and VGG16. The results show that the recommended model performs more accurately than any other model [7]. In this paper, the primary goal was to use a convolutional neural network (CNN) to automatically classify different date palm fruit kinds based on two key factors: color variation and date morphological parameter evaluation. The choice of classification standards affected the validation accuracy of the model described in this work. It was 85.24% for fruit color-based categorization and 87.62% for geometric features alone; however, when dates' color and morphology were taken into account, the percentage rose significantly to 93.41% [8]. The author used machine learning techniques i.e. KNN, SVM, and CNN to classify dates in 3 classes over 3383 images of Date and achieved 99% accuracy [9]. VGG-16 has also been used but it wasn’t futile as it gave an accuracy of 96.98% with only two classes over only 1300 images [10].

The author used Computer vision and pattern recognition to classify Date fruit into 7 classes over the dataset of only 140 images and gained 99% accuracy [11]. A method of automatically categorizing various types of dates from their images was proposed by the author in this study. A color image of a date is broken down into its individual color components in the suggested manner. The date's texture structure was then encoded by applying a local texture descriptor, such as a Weber local descriptor histogram or a local binary pattern, to each element. To characterize the image, the texture patterns from each component were combined. The feature set's dimensionality was decreased by using feature selection depending on the Fisher discrimination ratio. To completely characterize the date, size, and form features are added to the texture descriptors. The author then employed SVM as a classifier and achieved an accuracy of 98% [12]. This work [13] utilized computer vision and deep learning methods, the author of this research presented a smart harvesting decision system to evaluate the category, maturity level, and size of date fruits. Three sub-systems make up the proposed system: the dates weight estimation system, the types estimation framework, and the dates maturity estimation method. Four DL architectures were used: ResNet, Inception-V3, VGG-19, and NASNet for support vector machines and DMES and DTES, respectively. The predicted expansion in the probable spreading zones of date palms under present and future climatic conditions was estimated using the CLIMEX model. According to the model, there is a substantial amount of land (71.21%) that is appropriate for date palm agriculture given the current climate [14].

Using a set of extensive aerial and UAV-based images, many vision transformer models were generated and assessed. The deep vision transformers' adaptability and universality were assessed and contrasted with several CNN-based semantic segmentation techniques. When modeling date palm trees from UAV images, the studied deep neural networks produced excellent outcomes, with a mIoU that varied from 85% to 86.3% and a mF-score varying from 91.62% to 92.44% [15]. This research offers a newly developed, precise technique for separating healthy date fruit from faulty ones. Furthermore, because deep CNN is employed, this technique was used to predict when healthy dates will ripen. The proposed CNN model was constructed with max-pooling dropping out, batch normalization, and dense layers on top of the VGG-16 architecture. To train and assess this classifier, a picture dataset with four classes Khalal, Tamar, Rutab, and erroneous date was utilized. The dataset concerned camera parameters such as focus and stabilization and was collected with a smartphone under uncontrolled lighting conditions. The CNN approach achieved 96.98% classification accuracy overall. This study was conducted to assess the solution's capabilities and prove its feasibility. Their specific goal was to recognize the many kinds of dates fruits by using pictures of palm palms along with dates. Three CNN models were used to classify fruit and leaves: the first one identified the species of leaves, the second one classified the types of fruit, and the third one classified fruit and leaf pictures [16]. This study presents a brand-new method for evaluating date fruits that were considered both texture and form attributes. The method initially reduces the specular reflection and small noise using a bilateral filter. Threshold-based segmentation is used to extract the fruit component and eliminate the background from the given picture. Date fruit contours are used to extract shape characteristics, and local binary patterns and the curvelet transform are used to recover texture features from the chosen date fruit region. Ultimately, the dates are graded into six categories by fusing qualities related to shape and texture. When contrasted with two other classification algorithms, such as SVM and LDA, the KNN classifier produces the best grading rate. The results of the study demonstrate that our method gets the best results [17].

Moreover, support vector machines, random forests, K-Nearest Neighbours, and a few additional machine learning approaches Date fruit has been graded using these methods. As a result, date fruit categorization and sorting issues are now widespread in the sector. Date fruit categorization and grading required a well-organized dataset. An innovative and native dataset of date fruit is provided in this paper. Four types of date fruit are seen in the photographs in the dataset. It is made up of 3004 already processed photos from various grades and classes [18-22]. Pourdarbani et al. [23] also used classification in conjunction with color and texture analysis, including contrast, entropy, and date uniformity, to classify the maturity of date palm fruit of a single variety. Hobani et al. [24] suggested a date categorization system that utilized artificial neural network technology.

Zhang et al. [25] employed color analysis and backpropagation to categorize the ripeness of dates of a single variety. The technique outlined uses 2D colour histograms within different grading categories to determine the co-occurrence frequency, which serves as the foundation for colour analysis. This study produces a mapping matrix that makes it easier to backproject the colours of the input fruit to predetermined colour indices. After that, the colour indices that are produced are examined to determine the date colour, which is a crucial measure of quality and maturity. Using Medjool date grading as an example, the algorithm's effectiveness is shown, demonstrating both accuracy and user-friendliness. Additionally, the technique is flexible and simple to modify for grading applications in different fruits and vegetables. The date maturity evaluation method has been successfully applied to commercial date production. Depending on the type, Haidar et al. [26] divided photos of individual fruits into seven classifications using size, shape, color, and texture. Muhammad [27] employed shape, size, and texture criteria, just like his forebears, to differentiate four groups of dates according to images of individual dates.

The focus of this study is to develop a robust system that can be used for classification in any condition and on anything, date fruit was chosen because of its limited features and diverse types. For this purpose, 6 classes having almost 1300 images for every class are used in this study.

## 2. Materials and Methods

This section discussed the different steps included for the Date fruits classification The 1st step is the data selection, preprocessing, features extraction/classification, and then the performance measures have been discussed. The basic step for the classification of the Date is shown in Figure 1.

The Fruit Dataset was designed to meet the requirements of a wide range of applications both before and after harvest. The two most common applications are automatic harvesting and visual production estimation. The dataset aimed towards these two applications. The initial set of shots consists of 8079 images of over 350 date clusters collected from 29 date palms. Five different types of dates are Naboot Saif, Khalas, Bari, Meneifi, and Sullaj. [28], data is availabe on IEEE dataport. A new class consisting of 1158 images of the Dates of Ajwa variety is introduced by us to make the dataset more versatile and reliable. Images of the date clusters were taken using a color camera over six imaging sessions. The imaging sessions included all stages of date maturity: immature, Khalal, Rutab, Ajwa, and Tamar.

For feature extraction and classification purposes deep learning on the Sequential CNN neural model and ResNet50 have been utilized for the analysis of the results.

Alex Net took first place in the LSVRC2012 rating competition in 2012. The most exciting thing that happened to the computer world and the area of deep learning after that was ResNet. It was feasible to create ultra-deep neuron networks using the infrastructure provided by ResNets. That is, hundreds or thousands of layers can be carried while still achieving great performance. The first time ResNets were used was for image recognition [29]. Many argued that just stacking more layers improves understanding of why residual learning is required for the construction of ultra-deep neural networks. Deep convolutional neural networks, as we all know, are fantastic for detecting low, medium, and high-level properties in images. While stacking more layers typically improves precision, a follow-up issue is whether improving model performance is as simple as stacking more layers. The authors solved this challenge by using a deep residual learning framework to create short-cut links that only execute identity mappings.

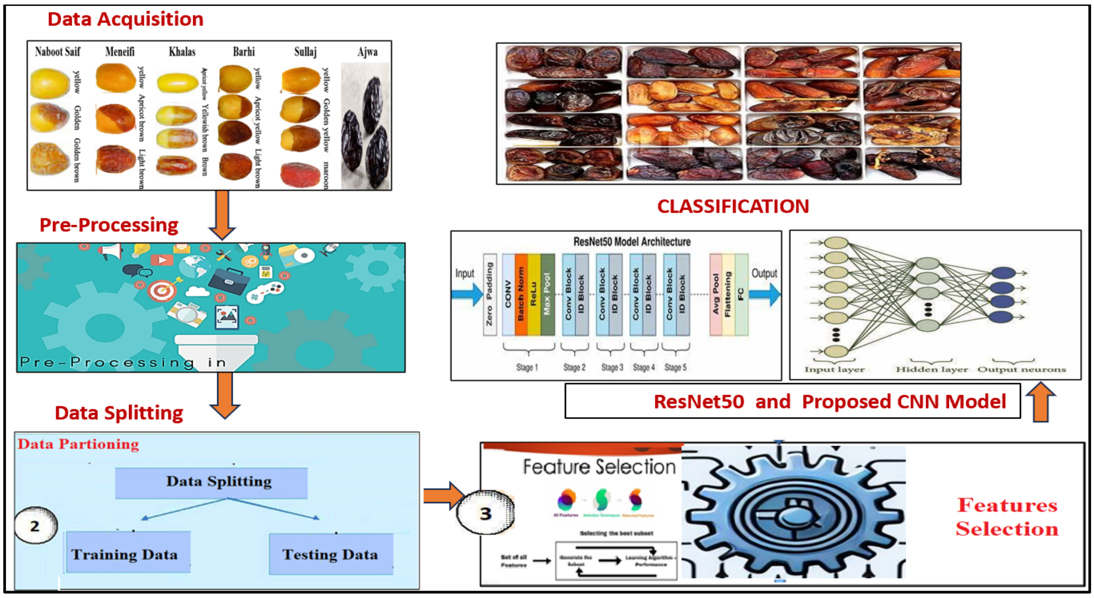


**Figure 1.** The basic step for the classification of Dates using the Deep learning model.

There was a minor adjustment made for ResNet 50 and higher since the shortcut connections were previously bypassing two tiers. However, they now skip three levels and have added a 1 * 1 convolution layer.

A convolutional neural network (CNN) is a deep learning system that can process an input image. Differentiate various items in the image by assigning priority (weight and bias) to them and being able to identify them apart. The amount of pre-processing required by a ConvNet is much less than that required by other classification techniques. While filters are embedded into simpler techniques, with enough training, ConvNets can learn such filters/features. A ConvNet's architecture is based on the visual cortex's organization and is similar to the neural connection model in the human brain. Individual neurons only respond to inputs in the receptor field, which is a tiny portion of the visual field. A set of these overlapping fields covers the visual zone.

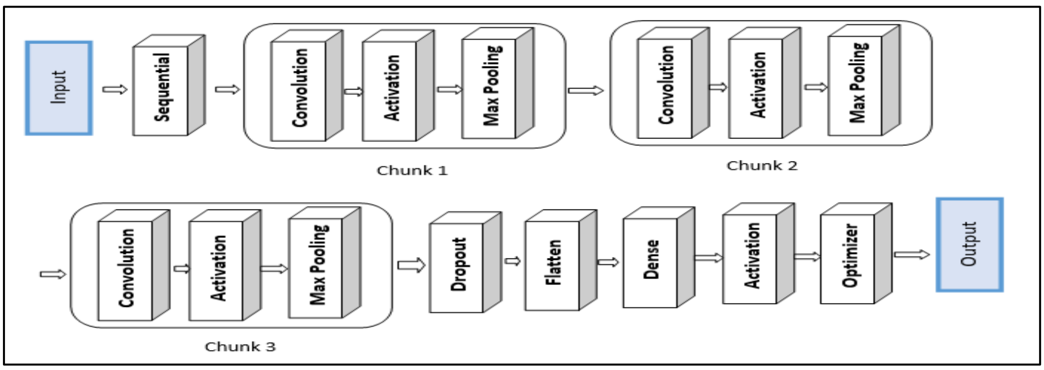


**Figure 2.** Proposed Sequential CNN Architecture

A ConvNet may successfully capture spatial and temporal correlations within an image by applying the relevant filters. The design adapts better to the picture data set due to the decreased number of parameters and the reusability of the weights. To put it another way, the network might be constructed in order to better comprehend the complicated visual.

The pooling layer, like the convolutional layer, is in charge of decreasing the convoluted feature's spatial size. To decrease the processing resources needed to interpret the data, a dimensional reduction is performed. Extracting the dominant rotational and positional invariant properties is also important for maintaining the model's successful driving mechanism. Maximum pooling and average pooling are the two types of pooling. Max Pooling returns the maximum value for the proportion of the picture covered by the kernel. On the other hand, Average Pooling returns the average of all the values in the kernel's image section. To effectively learn and distinguish the types of date fruits with high accuracy, a convolutional neural network (CNN) was constructed and trained from scratch. CNN Architecture was improved with a combination of Convolutional, Activation, and Max Pooling layers. The basic structure of Sequential CNN Model Details is discussed in Table 1.

**Table 1.** The basic structure of Sequential CNN Model Details

| Sr. No | Parameters | Setting |
|---|---|---|
| 0 | Sequential | |
| 1 | Convolutional layer | Kernel size=3x3, Input Shape= 64x64x3 |
| 2 | Activation | (ReLu) Rectified Linear Unit |
| 3 | Max Pooling | Size 2x2 |
| 4 | Convolutional layer | Kernel size=3x3, Input Shape= 32x32x3 |
| 5 | Activation | (ReLu) Rectified Linear Unit |
| 6 | Max Pooling | Size 2x2 |
| 7 | Convolutional layer | Kernel size=3x3, Input Shape= 32x32x3 |
| 8 | Activation | (ReLu) Rectified Linear Unit |
| 9 | Max Pooling | Size 2x2 |
| 10 | Dropout | 0.25 |
| 11 | Flatten Layer | |
| 12 | Dense Layer | Unit= 5 |
| 13 | Activation | Softmax |
| 14 | Optimizer | Adam |
| 15 | Loss | Sparse Categorical Cross Entropy |
| 16 | Metrics | Accuracy, Precision, Recall, F1-measure |

Max Pooling works as a noise reduction as well. It rejects every noisy activation while simultaneously de-noising and dimensional reduction.

Average pooling, on the other hand, is only a dimensionality reduction approach for noise suppression. As a consequence, it may be said that Max Pooling performs better than Average Pooling. The convolutional layer and the clustering layer make up the i-th layer of a convolutional neural array. Depending on the complexity of the image, the number of these layers may be increased to collect even more low-level information, but this requires more processing power.

Following the preceding stages, the model is able to understand the properties. The final output will then be flattened and fed into a traditional neural network for classification.

## 3. Results

The results have been compared by using the proposed CNN model and with a pertained model ResNet50. The data was separated into two parts: 70% and 30%. Seventy percent of the dataset is utilized for training, whereas thirty percent is used for testing. F1-Score, precision, average loss, recall, and accuracy parameters are used to show results by using graphs and tables [30]. A weighted average of the true positive (recall) and accuracy scores is used to determine the F1 score.

$$\text{F1\_measure} = \frac{2 * Precision * Recall}{Preciosion + Recall}$$

The precision metric depicts the positive class's precision. It calculates the probability that the positive class's forecast is right.

$$\text{Precision} = \frac{TN}{TN+FP}$$

Sensitivity is the ratio of accurately recognized affirmative classifications. The model's ability to distinguish a positive class is measured using this metric.

$$\text{Sensitivity } (Recall) = \frac{TP}{TP+FN}$$

A machine learning algorithm's accuracy is a typical criterion for judging its worth. As shown in the following equation, accuracy is defined as the number of properly identified outputs.

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

3.1 ResNet50 Model of Classification

In this section only one pre-trained model whose results are better than all other other pre-trained models have been shown.

First calculated the results of the pre-trained model ResNet50. The Accuracy, Precison, Recall and F-easure have been calculated and discussed in Table 2.The following figure shows the model accuracy of the ResNet50 pre-trained model in Figure 3. The comparisons of the Results by using different Epochs have been shown in Figure 4.

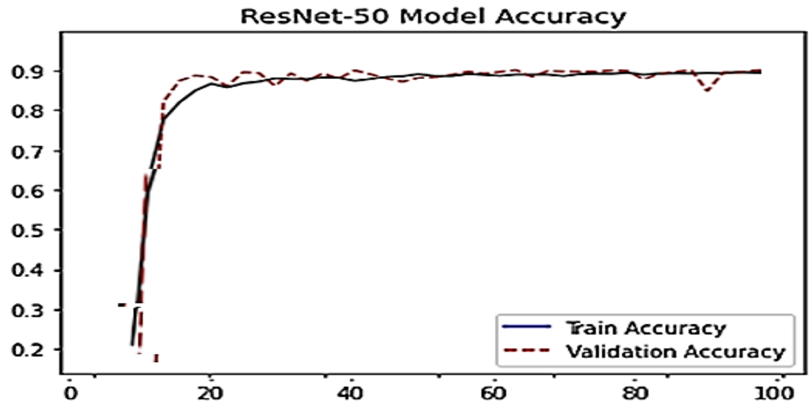


**Figure 3.** Accuracy Using ResNet50 Model of Classification

**Table 2.** Accuracy, Precision, Recall and F1-score results using ResNet50.

| Epochs | Accuracy | Precision | Recall | F1Score |
|---|---|---|---|---|
| 20 | 86.86 | 92.16 | 78.65 | 84.67 |
| 40 | 90.89 | 94.06 | 86.71 | 90.11 |
| 60 | 93.22 | 95.15 | 90.73 | 92.82 |
| 80 | 95.66 | 97.36 | 93.27 | 95.20 |
| 100 | 94.92 | 96.06 | 93.22 | 94.57 |

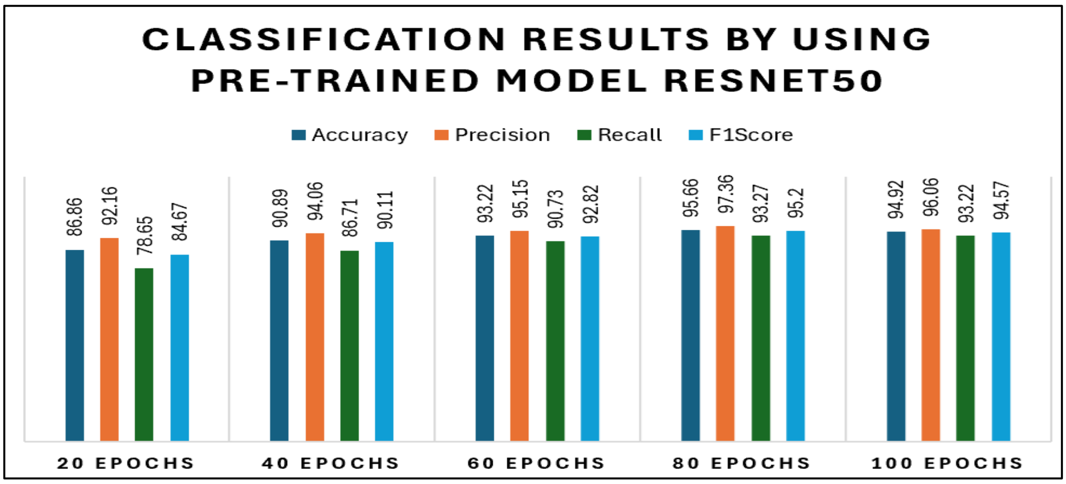


**Figure 4.** Comparisons of the Results by using different Epochs.

3.2 Results Using Sequential CNN Model of Classification

Following figure shows the graph showing Training as well as Validation Accuracy of Sequential CNN Model.

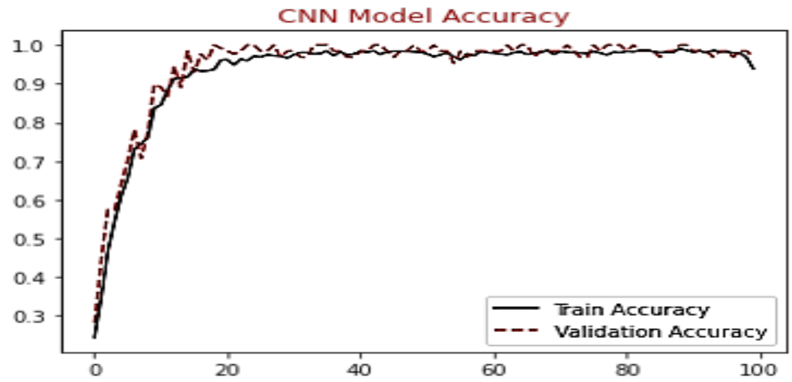


**Figure 5.** Accuracy Using Sequential CNN Model of Classification.

The precision, recall and F1 score for CNN classification are given in Table 3.

**Table 3.** CNN Classification Results

| Epoch | Accuracy | Precision | Recall | F1Score |
|---|---|---|---|---|
| 20 | 96.1 | 89.06 | 88 | 98.4 |
| 40 | 97.71 | 82.36 | 91 | 91.6 |
| 60 | 98.05 | 80 | 93 | 89 |
| 80 | 98.05 | 78.78 | 94 | 89.24 |
| 100 | 98.08 | 73.84 | 96 | 93.38 |

Classification results by using the proposed CNN model by using 20,40,60,80 and 100 epochs are represented in Figure 6.

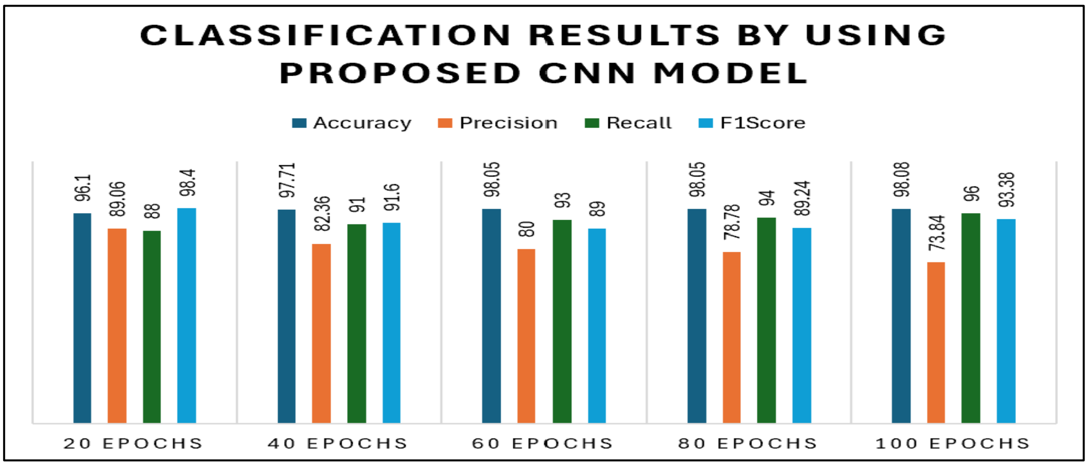


**Figure 6.** Classification results by using the proposed CNN model by using epochs.

All previous work done limits in one way or other high accuracy is achieved but less number of classes and small datasets. [36] achieved good results with a handsome dataset but the problem is expensive hardware was used which is not good for an on field environment.

**Table 4.** Comparison With Previous Work

| Author | Year | Technique | Accuracy | Classes | Images |
|---|---|---|---|---|---|
| [6] | 2020 | KNN, SVM, CNN. | 99% | 3 | 3383 |
| [18] | 2019 | VGG-16 | 96.98% | 2 | 1300 |
| [36] | 2019 | Transfer Learning. | 99.01% | 5 | 8072 |
| [19] | 2012 | Pattern recognition | 99% | 7 | 140 |
| [27] | 2018 | SVM | 100% | 2 | 120 |

| | | | | | |
|---|---|---|---|---|---|
| **Our Proposed Method** | ----- | ResNet50<br>CNN | 95.66%<br>98.08% | 6 | 9200 |

## 4. Discussion

One interesting use in the analysis of data and information extraction is the classification of date variety using deep learning models. The various ways that dates can be expressed in textual data are referred to as date variety, and these variations offer difficulties for conventional rule-based or pattern-matching techniques. Deep learning models provide a potential way to tackle these issues. The ability of deep learning techniques to automatically extract complex patterns and representations from the input data is one of its main benefits in the categorization of date varieties. Although deep learning models show great potential, managing noisy or unclear date representations presents difficulties. When evaluating how well deep learning models perform in the categorization of date varieties, evaluation measures are essential. Metrics like recall, accuracy, precision, and F1-score shed light on how well the model can recognize and categorize various date formats. Model performance may be further optimized by adjusting hyperparameters, experimenting with alternative architectures, and considering ensemble approaches. The pre-trained model ResNet50 achieved on the selected datasets having six classes was 95.66% accuracy while CNN performed well as it got 98.08% accuracy it has also a plus point of simplicity that results in fast yet efficient classification.

There is a need to build a more comprehensive dataset of Date Fruit having more classes as date fruit has more than 600 types with more images per class the second area to work on is the development of a more powerful model that can achieve higher accuracy with such a challenging Dataset. Work is also needed in the area of the development of real-time systems that can automate the date processing process.

## 5. Conclusions

One major step towards resolving the issues raised by the many and frequently complex ways in which dates are represented in data is the categorization of date variety using deep learning models. A real-time machine vision system for date fruit type identification in an orchard scenario was proposed based on deep learning. A model for categorizing date fruit into distinct categories was incorporated into the framework.

The proposed method is very helpful when it comes to a large and diversified dataset. Its result has shown that it can be classified based on very limited features. About 1400 to 2100 images per class were used and achieved 98.08 % accuracy using Sequential Convolutional Network while 95.66% using ResNet50 which has not been achieved with such a large number of a dataset comprising 9237 images of six different varieties and was randomly divided 70% for training and 30% for validation. The dataset used was carefully developed to encounter the real-time problems that a farmer faces while harvesting and categorizing the dates.

The proposed method i.e. Sequential CNN provides the best accuracies with normal hardware to the best of our knowledge.

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