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Date Fruit Classification Model Using Deep Learning

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Abstract

Date fruit, which comprises nearly 80% of fruits produced in the Sultanate of Oman, is the leading agricultural crop in the country. Sophisticated technologies are utilized to improve the date fruit production in the country, but date sorting and grading after post-harvesting still create problems for the date cultivators. Manual date sorting is a time-consuming process and raises ambiguity about the accuracy and consistency of the grading system. This paper presents a date fruit classification system based on deep learning. It categorizes dates into four different classes based on their physical attributes. Dates fruit classification in automatic mode is challenging due to its high visual similarity, and getting better grading accuracy and performance evaluation, numerous combinations of hidden layers and epochs have been done. The performance of the model is evaluated based on its accuracy and losses. The model performance is appreciable, with a validation accuracy of 97.2%.

Index Terms—Convolutional Neural Network (CNN), Dates fruit classification, Fruits grading, Hidden layers, Image Recognition

Introduction

Dates fruit is a rich resource of carbohydrates and contains a considerable number of vitamins, fibers, and minerals. It provides fitness and strength to the human body and cures diseases like stomach upsets, memory disorders, etc. [1]. In the world of dates production, Oman is ranked 9th, with 80% of its fruit crops belonging to dates [2,3]. Nearly 50% of the dates cultivated in the country are used for human intake, whereas the remaining half is considered animal food or wasted [4,5]. Even if Oman's most significant export product is dates fruits, it constitutes only 2.6% of the total production. Analysis shows that poor post-harvest handling of dates is one reason for this low export rate. Omani dates are fetching lower prices in the international markets compared to other countries [4].

Maximizing the return from date palm is very important as it touches the lives of the nationals. Recovery from data harvesting depends on its post-harvest processing system. An efficient classification and storage system enhances the market and hence the export of the fruits. Various dates are cultivated in Oman, and they are different in shape, size, texture, and color. The hardness and shape of the same dates class vary due to their maturity level. They vary in taste and hence in cost. Some varieties are easily distinguishable by visual appearance, while others are difficult to categorize, even for a specialist. Traditionally date classification is done by visual inspection of human labor. But such a system takes a long time, and the accuracy of the category varies from labor to labor and even goes as his mood fluctuates. So, a sophisticated dates processing and handling system is an inevitable thing for uplifting the nation's income and hence the country's GDP.

Quality factors used in a grading system directly affect the system's accuracy. Factors used for fruit grading can be classified into two categories: internal and external quality factors [7]. Visual appearance and factors such as color, shape, size, etc., contribute to the external factors. The sweetness of the fruit, its smell, flavor, taste, etc. defines the internal quality factors. Some factors like toughness, crispness, firmness, etc. can be considered as internal or external quality factors. If the grading is based on internal quality factors, it can be either a destructive approach or a non-destructive approach. In a non-destructive approach, during the grading process, spectroscopic and hyperspectral imaging techniques are used, and the quality of the fruits is not affected [7,8].

Nowadays external quality-based fruits grading system is getting more attention due to its simplicity and practicality. Advancements in image processing and machine learning provide effective tools for automatic fruits classification. A detailed literature survey reveals that extensive research has been conducted in the image processing and machine learning sector for automatic fruit grading. The aim of the present study is to categorize dates fruits based on their physical attributes.

A. Related works

A comprehensive summary of the works in this area is explained in this section. Abdulrahman et al. [9] developed a computer vision-based dates fruits classification system that works based on the image RGB value. The vision-based system was able to classify selected fruits into three different categories. Yousuf et al. [7] described a computer vision-based dates sorting system. The demonstrated system consisted of a fruits quality analyzer and categorizing mechanism. A motor-driven conveyer belt provides the movement of the dates from the input section to the imaging section. Using the RGB images of the collected fruits, they set some quality features. Based on the quality factors, the acquired image quality is analyzed using an algorithm and the accuracy of the system is evaluated using the backpropagation algorithm. Joseph et al.[10] discussed a system for date fruit grading based on its maturity level. The physical attribute of the fruit like color varies based on its maturity level. Based on this concept, they developed a system for sorting dates fruits using a conveyor belt and machine vision. Results show that validation by experts and the system response for khalal and Tamar classes was almost acceptable. Ismail et al. [11] developed a system to measure the moisture content in dates using electronic sensors and hence classify the fruits as moist, medium, and dry. Aiadi [12] et.al developed a machine learning-based date's classification system using a Gaussian mixture model for representing the date variety. Calinski-Harabasz index was used to perform optimal clustering of the dates. Mohana et al. [13] described the date's fruit classification algorithm based on computer vision. The classification was based on the texture properties and the shape of the fruits. Segmentation of the fruits from the background was done using a threshold-based approach and contour mapping. LBP map was used for the extraction of the fruit's texture details. Grading of the fruits into six classes was achieved by the fusion of shape and texture details using the k-NN classifier. Kumaravel et al. [14] described a fuzzy logic control-based date’s classification system. The size and shape of the fruits are estimated using the ultrasonic sensor reading. Based on the sensor data, the attached microcontroller sends signals to the fruit-dropping system. Tianmei et al. [15] presented a simple CNN for the classification of images. Analysis of the learning rate set and optimization algorithm for image classification was discussed. Nishi et al. [16] presented an image grading system using the RGB-D concept. The grading process is performed based on the size of the input object image and CNN is used for accomplishing the process.

Visual image recognition is one of the most important components of automated control systems and decision-making systems [3]. Advancement in communication and decision-making systems plays a major role in today's automated industries. Recently machine vision-based image identification and classification technique have got wide acceptance in the research and industry sector. Convolutional neural network (CNN) is considered one of the widely used deep learning techniques in artificial neural networks [17, 18]. A convolutional neural network is an artificial neural network that is widely used for the smart processing of image data such as pattern recognition, classification, etc. CNN architecture is inspired by the biological model of the mammalian visual system. CNN architecture contains three main layers: convolutional, pooling, and output layer [10, 19]. CNN abstracts spatial and local features precisely from the input data such as images and video.

In the CNN network, the stack of convolutional and pooling layers constitutes the feature learning layers [20, 21]. These layers extract the image feature and feed the data to the fully connected classifier layer. The fully connected classification layer (output layer) uses these features for classifying the input image. In the date’s classification process, within a class, the physical attributes of dates may slightly vary, and the image intensity also varies. The system should be invariant to such intraclass variations and at the same time, it should be sensitive to interclass variations. The stacked convolutional-pooling layers perform the feature learning task. The extracted features are coupled to the flatten layer, which converts the 2-D filtered image matrix into a 1-D feature vector. The classification based on the extracted features occurs in the dense layer.

Image classification operation can be divided into feature learning section and classification section. Compared to other image-recognizing architectures, CNN requires less memory for storing the extracted features and is invariant to distortions due to camera rotation or shifts in the horizontal or vertical directions, etc. Performance of CNN in image classification is far better compared to other ANN structures [17].

The remainder of this paper is organized as follows. The proposed model and basic concepts of CNN are presented in section 2. In section 3validation results of the proposed model are presented. The conclusion of the study is presented in section 4.

Materials and methods

The proposed system classifies the input date fruits into one of the four categories based on its physical attributes. This system is built based on CNN which takes single input at a time and classifies the fruit into one of the four possible outputs.

B. Convolutional Neural Network (CNN)

CNN is an artificial neural network widely used for the smart processing of image data. Figure 1 shows the general architecture of a CNN for the classification of images. It has a layered architecture. The first hidden layer in a CNN is the convolution layer and it works as the basis of the CNN. A convolutional layer receives the input, transforms the received inputs to the required format, abstracts the image features, and output it to the next layer. The convolutional layer is followed by the pooling layer. The pooling layer downsamples the spatial resolution of the image while keeping the spatial invariance in the image. The conversion of 2-dimensional image to 1-dimensional array is performed by the flatten layer. The neurons in the fully connected output layer receive inputs from all neurons in the previous layer and are trained based on the error backpropagation concept. In the proposed system, the output layer consists of two fully connected layers that classify the input image into one of the four classes. The softmax activation function facilitates multiclass fruit classification. Fig.1. shows the schematic CNN architecture for the proposed dates classification system.

C. Convolutional layer

Convolution layer is used to extract the features in the input image. The set of filters arranged in this layer mines the image features like circles, corners, edges, etc. The input image is represented as a 2-D array of pixel values. Instead of the fully connected neural network, patches of the input are connected to a single neuron in this layer. So only a small region of the input image is influencing this specific hidden layer neuron. This is accomplished by sliding a patch window over the input image. When the convolutional layer receives input, the selected filter called kernels slides over each n x n set of pixels in the input image until it slides over every n x n block of pixels in the entire image. In the case of a 3 x 3 filter, the filter convolves along each 3 x 3 block of pixels in the input image. This process retains all the spatial information inherent to the image. To learn the visual features inherent in the image, instead of providing a uniform connection between the patches and the hidden layer neurons, a weighted connection is provided. This process is called convolution.

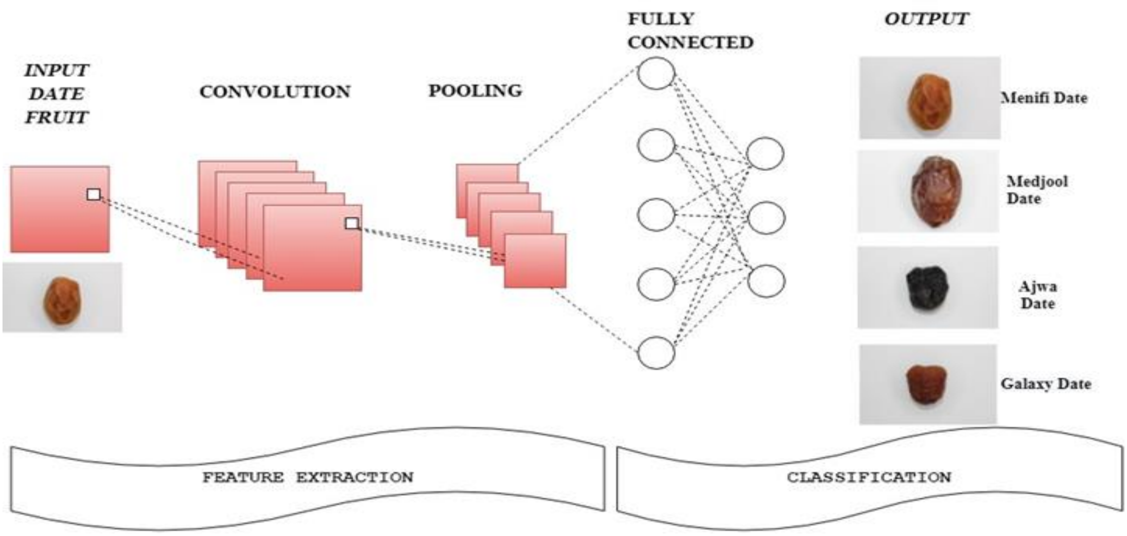

Fig.1. *Schematic CNN architecture for the proposed date's classification system*

The 2-dimensional convolution on the input image can be represented by the mathematical equation

$$y[p, q] = \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} h[i, j] . x[p - i, q - j] \quad (1)$$

Where x represents the matrix representing the input image, h represents the filter matrix called kernel matrix and y represents the convolved result, representing the image output.

The convolution operation is explained in Fig. 2. The 5 x 5 matrix given represents a patch of the input image. The 3 x 3 matrix acts as the filter to extract the feature. The filter slides over the 5x5 matrix and element-wise multiplication and adding the output of each patch occurs.

When the filter lands on the first 3 x 3 block of pixels, the dot product of the filter coefficients and the pixel values are calculated and stored. Here the convolution results in 4 as the first entry of the output matrix. This is called the feature map. Now the filter slide over the entire image and repeats the same process. By changing the weight of the filter and using different filters, different features of the image can be extracted. Each neuron in the convolution layer takes input from a single patch. It computes the weighted sum of the inputs from that patch and applies bias as in (2). Each hidden neuron is seeing only a patch from the input image.

$$f(x) = \max(0, x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases} \quad (2)$$

D. Pooling layer

The convolutional layer is coupled to the pooling layer. In the convolution layer the non-linear activation function ReLu gives a nonlinearity in the operation[22,23]. Mathematical representation of a ReLu faction is given in equation 2. It replaces all negative values of the pixel intensity by zero and pixel intensity greater than zero keeps as the same.

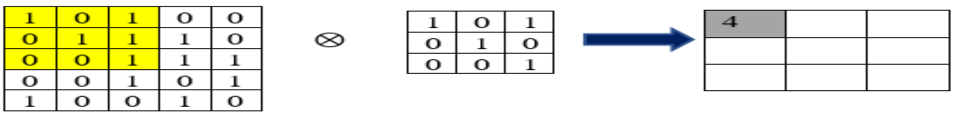

Fig.2. *Convolution operation*

The pooling operation reduces the dimensionality of the input layer. It can be max pooling or average pooling. In max-pooling, the maximum value of that patch is taken whereas, in average pooling, the average value of the corresponding patch is considered. It picks a window size of 2 x 2 or 3 x 3 and slides over the filtered image. Usually, convolutional layers and pooling layers exist in a pair form. The moving steps of the kernels determine the size of the feature map in the pooling layer.

E. Flatten layer

The extracted features are coupled to the flatten layer, which converts the 2-D filtered image matrix into a 1-D feature vector.

The proposed CNN structure consists of three pairs of convolutional and pooling layers, flatten layer, and two dense layers at the output. The first convolutional layer constitutes the first hidden layer which has 16 filters with 3 x 3 kernel size. The second and third convolutional layers contain 32 and 64 filters respectively. In all convolutional layers, ReLu is used as the nonlinear activation function. Max pooling is applied in the proposed system. In this paper, 2 x2 patches are taken. From each window, it takes the maximum value. This operation shrinks the spatial dimensionality from 4 x4 to 2x2. Convolution and pool layers abstract the high-level features of the input image.

The classification based on the extracted features occurs in the dense layer. In the proposed system, the output layer consists of two fully connected layers that classify the input image into one of the four classes. The softmax activation function provides multiclass fruit classification.

The activation function used at the fully connected output layer is softmax which expresses the output as the probability of image belonging to a particular class. The mathematical representation of the softmax is

$$\mathrm{softmax}(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}} \quad (3)$$

One of the factors that affect the efficiency of the training process is the error function, which can be optimized by optimizers. The algorithm that changes the attributes like learning rate, weight, etc. to reduce the error function is called optimizer. The proposed system compares the system performance using RMSprop and Adam optimizer.

F. Data set

The first step in the machine learning approach is collection of image data set for training, testing, and validation of the classification model. The data set for the analysis of the proposed model is taken from [24]. Fig.4 shows the samples from the dataset.

The data set consists of 1028 date's images that belong to four different classes. This paper considers four types of dates: ajwa, galaxy, meneifi and medjool for the grading process. These dates' classes are represented in figure 3. The data set available is classified into three classes, training, testing, and validation set. Nearly 70% of the images from each class is included in the training class and the remaining 30% in the testing class. A validation set is used to evaluate the model during the training. This helps the proper validation of each class by testing enough images from all date's class.

Fig. 3 *sample of different types of date fruits*

G. Training the model

The training procedure optimizes the parameters of the different layers to minimize the difference between the predicted output and the training set labels. During the training process, the input image taken in batches pass through the network, and the error between the actual and predicted output is calculated. The updating of the weight continues till the calculated difference reaches the predetermined minimum value.

The weight, w, is updated based on the equation

$$w_j = w_{j-1} - \alpha \frac{\partial E}{\partial w} \quad (4)$$

Where

$$E = \sum (\text{expected output} - \text{predicted})^2 \ (5)$$

For the accurate classification, the training data should be large, otherwise, it may lead to overfitting. To prevent this overfitting, the training data set is image augmented in different ways like reflection and translation. In image augmentation, the training set randomly undergoes horizontal reflection, horizontal or vertical scaling or vertical translation, etc.

Result and discussion

For date's classification, the dataset contained 1028 dates' images of 4 classes. Each class was of a different size and the images were resized before giving for training. We selected four types of dates: ajwa, galaxy, meneifi and medjool for the grading process. The model was trained with different epochs using the RMSprop and Adam optimizer with steps per epoch size of 10. Fig.4 shows the output obtained for different classes of input applied.

Table1 shows the details of validation accuracy and validation loss for RMSprop optimizer with a learning rate of 0.001 for different epochs.

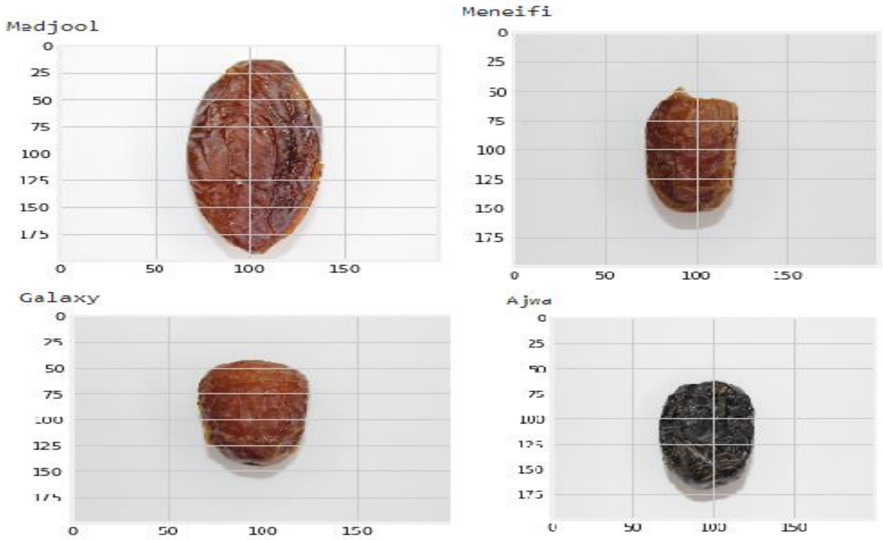

Fig. 4. *Output of the proposed classifier model*

Table 1: *Performance details of the proposed model for RMSprop optimizer*

Sl.No	Number of epochs	Validation accuracy	Validation loss
1	1	0.8093	0.7942
2	10	0.9163	0.3868
3	20	0.9488	0.2250
4	30	0.9651	0.1010

Table 2 shows the details of validation accuracy and validation loss for Adam optimizer with a learning rate of 0.001 for different epochs.

Table 2: *Performance details of the proposed model for Adam optimizer*

Sl.No	Number of epochs	Validation accuracy	Validation loss
1	1	0.8093	0.7942
2	10	0.9535	0.1615
3	20	0.9653	0.1116
4	30	0.9721	0.0984

The graphical representation of validation accuracy and validation loss for Adam optimizer with a learning rate of 0.001 for different epochs is shown in Fig.5.

The graphical representation of validation accuracy and validation loss for RMSprop optimizer with a learning rate of 0.001 for different epochs is shown in Fig. 6.

A deep learning-based dates fruits classification model was proposed in this paper. For dates classification, the dataset contained 1028 dates images of 4 classes. Each class was of different sizes and the system used four types of dates: ajwa, galaxy, meneifi, and medjool for the grading process. The model was trained with different epochs using the RMSprop and

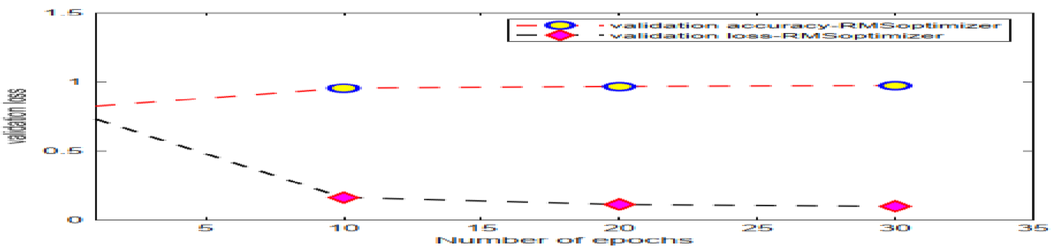

Fig.5. *Performance details of the proposed model for Adam optimizer*

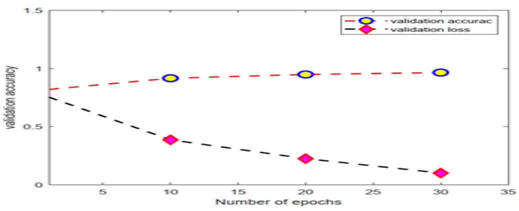

Fig.6. *Performance details of the proposed model for RMSprop optimizer*

Adam optimizer with steps per epoch size of 10. The proposed model attained

References

Al-Hooti, S., Sidhu, J.S. and Qabazard, H. (1997) ‘Physicochemical characteristics of five date fruit cultivars grown in the United Arab Emirates’, Plant Foods Human Nutrition, Vol. 50, No. 2, pp.101–113.

Hamdi Altaheri, Mansour Al Sulaiman, Ghulam Muhammed,” Date Fruit Classification for Robotic Harvesting in a Natural Environment Using Deep Learning”, IEEE Access

Z. M. Khaing, Y. Naung and P. H. Htut, "Development of control system for fruit classification based on convolutional neural network," 2018 IEEE Conference of Russian Young

Researchers in Electrical and Electronic Engineering (EIConRus), 2018, pp. 1805-1807, doi: 10.1109/EIConRus.2018.8317456

Rashid Al-Yahyai and M. Mumtaz Khan," Date Palm Status and Perspective in Oman", Springer Science Business Media Dordrecht 2015 207 J.M. Al-Khayri et al. (eds.), Date Palm Genetic Resources and Utilization: Volume 2: Asia and Europe, DOI 10.1007/978-94-017-9707-8_6.

https://unctad.org/system/files/non-official-document/ditc-ted-21032018-oman-squ-15-Mbaga-Evaluation.pdf.

Deepali M Bongulwar, "Identification of Fruits Using Deep Learning Approach", IOP Conf. Series: Materials Science and Engineering, doi:10.1088/1757-899X/1049/1/012004

Yousef Al Ohali, " computer vision based date fruit grading system: Design and implementation", Journal of King Saud University, Computer and Information Sciences, Volume 23, Issue 1, January 2011, Pages 29-36

Slaughter, D.C., Thompson, J.F., Tan, E.S., 2003," Nondestructive determination of total and soluble solids in fresh prune using near infrared spectroscopy", Postharvest Biology and Technology 28, 437–444.

Abdulrahman S. Alturki, Muhammed Islam, Mohammed F. Alsharekh, Mohammed S. Almane, and Anwar H. Ibrahim, Date Fruits Grading and Sorting Classification Algorithm Using Colors and Shape Features, International Journal of Engineering Research and Technology. ISSN 0974-3154, Volume 13, Number 8 (2020), pp. 1917-1920 © International Research Publication House. http://www.irphouse.com

Joseph J.L., Kumar V.A., Mathew S.P. (2021) Fruit Classification Using Deep Learning. In: Mekhilef S., Favorskaya M., Pandey R.K., Shaw R.N. (eds) Innovations in Electrical and Electronic Engineering. Lecture Notes in Electrical Engineering, vol 756. Springer, Singapore. https://doi.org/10.1007/978-981-16-0749-3_62

K. M. Ismail and K. A. Al-Gaadi, "Development of an electronic sensor for Date sorting based on moisture content," Misr J. Ag. Eng, vol. 26, no. 4, pp. 1923–1932, 2009

Aiadi, O. and Kherfi, M.L. (2017) 'A new method for automatic date fruit classification', Int. J. Computational Vision and Robotics, Vol. 7, No. 6, pp.692–711.

Mohana S.H. and Prabhakar C.J., A Novel Technique for Grading of Dates Using Shape And Texture Features, Machine Learning and Applications: An International Journal (MLAIJ) Vol.1, No.2, December 2014

Kumaravel. G., Ilankumaran. V., Suaad Abdullah Al Maqrashi, Manar Khalifa Saif Al Yaaqubi., Automated Date Fruits Sorting Machine using Fuzzy Logic Controller, International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8, Issue-4, November 2019.

Tianmei Guo, Jiwen Dong, Henjian Li˙Yunxing Gao, Simple Convolutional Neural Network on Image Classification, 10.1109/ICBDA.2017.8078730

Nishi, S. Kurogi and K. Matsuo, "Grading fruits and vegetables using RGB-D images and convolutional neural network," 2017 IEEE Symposium Series on Computational Intelligence (SSCI), 2017, pp. 1-6, doi: 10.1109/SSCI.2017.8285278.

Shadman Sakib, Zahidun Ashrafi, Md. Abu Bakr Sidique, Implementation of Fruits Recognition Classifier using Convolutional Neural Network Algorithm for Observation of Accuracies for Various Hidden Layers, ArXiv e-Journal (ISSN 2331-8422)

Al-Shawwa Mohammed O., "Apple Fruits Classification Using Deep Learning", International Journal of Academic Engineering Research, Vol. 3 Issue 12, December – 2019, Pages: 1-6

Bindu P.V., Vanitha Mahadevan, Dua Hilal Al Salim Hashmi, Azhar Zahir Al Harrasi,"Multiclass fruit classification model using deep learning" ,International

Journal of Research and Analytical Reviews,December 2021, Volume-8, Issue-4, Pages 876-880.

Bhargava, A.; Bansal, A. Fruits and vegetables quality evaluation using computer vision: A review. J. King Saud Unive. Comput. Inf.Sci. 2018, in press. Available online: https://doi.org/10.1016/j.jksuci.2018.06.002 (accessed on 5 June 2018).

Rachmawati, E.; Supriana, I.; Khodra, M.L. “Toward a new approach in fruit recognition using hybrid RGBD features and fruit hierarchy property” In Proceedings of the 2017 IEEE 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), Yogyakarta, Indonesia, 19–21 September 2017; pp. 1–6..

Pourdarbani, R. et al., Study on an automatic sorting system for Date fruits. Journal of the Saudi Society of Agricultural Sciences (2013), http://dx.doi.org/10.1016/j.jssas.2013.08.006

Myongkyoon Yang, Seong In Cho, “Fruit Classification using Convolutional Neural Network (CNN)”, Precision Agriculture Science and Technology, DOI: 10.12972/pastj.20210001.

https://www.kaggle.com/wadhasnalhamdan/date-fruit-image-dataset-in-controlled-environment?select=Ajwa.