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Apple fruits categorizing based on deep convolutional neural network techniques

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ABSTRACT

For a variety of reasons, including the high degree of similarity between varieties of the same type of fruit, the requirement to train the technique on a large amount of data, and the type and number of features suitable for application, the use of computer vision techniques in the classification of fruits still faces many challenges. Additionally, the technique's effectiveness and speed both need to be improved. Deep conventional neural network (DCNN) approaches were required for all of these reasons. A proposed include convolutional neural network (CNN) model is described in this work. The suggested methodology is intended to quickly and accurately categorize thirteen groups of apple fruits. The proposed technique was based on training and testing the model on a maximum number of images of apple fruits, by increasing the number of database images tenfold, after augmentation was performed on the images. The technology also relied on good tuning of the hyperparameters. To further ensure the efficiency of training, validation was performed on 20% of the database. All results that demonstrate the high efficiency of the proposed model were reviewed. The results of the proposal were compared with the results of four related techniques. The results showed the great advantage of the proposed technology at all levels.

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1. INTRODUCTION

The classification of fruits and vegetables [1]–[7] using computer vision techniques [8], [9], has become one of the important research topics, due to the discrepancy in prices between different types. The increased consumption of fruits and vegetables makes it necessary to increase the separation rate of the machine per hour. On the other hand, climate changes have caused the emergence of many diseases in different agricultural crops. Until now, the use of computer vision techniques in the classification of fruits still faces many challenges, for many reasons, including the great similarity between types of fruits of the same type, the need to train the technique on a large amount of data, and the quality and number of features suitable for application. This is in addition to the need to always improve the efficiency of the technique and increase its speed. All of these reasons led to the use of deep conventional neural network (DCNN) techniques [10]–[18] becoming necessary. Since machine learning techniques [19]–[28] are still not suitable for applications in which algorithm training is performed on a large amount of data, as well as applications in which a large number of classes are separated. So, recently, fruits are recognised from images using deep neural networks

(DNN), which are utilised in the field of image identification and classification. Compared to other machine learning methods, DNN performs better. Deep learning algorithms include convolutional neural networks (CNNs), which are categorised as such. CNN [29] are the most popular type of artificial neural networks (ANNs) used in deep learning [30]. In this paper, a proposed CNN model is presented. The proposed model is used for the purpose of classifying 13 types of apples with high accuracy. The proposed CNN model is designed to work by the best accuracy and with high processing speed. The proposed CNN method employed several hidden layer and epoch combinations for various scenarios in order to compare their classification accuracy results. The proposed method was applied to 64,040 images for model training, images belonging to 13 classes, 21,340 images belonging to 13 classes for modelvalidation, 21,340 images belonging to 13 classes for testing. In this section, a number of recent publications are reviewed and analyzed, which dealt with presenting proposals for techniques that contribute to the development of automatic separation of fruits and vegetables in general, and apple fruits in particular based using CNN techniques.

Sakib *et al.* [29] method that is suggested uses deep learning to categorize five different types of apples. Despite using a sizable database, the author assumed that the accuracy of the proposal would be assessed using a variety of performance evaluation techniques. He also did not compare the accuracy of his proposal's results to those of other proposals, the results of the processing speed were also not reviewed. This is in addition to the fact that his proposal is to classify only five types of apple fruits.

Risdin *et al.* [31] proposed technique is to classify four different types of fruits: grape, green apple, lemon, and lychee; based on the use of deep learning techniques. Although the author compared the results of the proposed performance accuracy test with the results of the performance accuracy test of similar techniques, and the proposed results are distinguished compared to the results of other techniques, it may be noted in this research paper the following: First, he used a simple database of only 2,403 images distributed over the four varieties. Secondly, fruits of the same type were not classified, but rather fruits of different types were classified, and this is easier to classify. It was more beneficial to implement a classification of fruits of the same type. Third, the author did not review the processing speed results of his proposed technique.

Yang and Cho [32] proposed technique is to classify seven different types of fruits: bell pepper, strawberry, orange, lemon, pomegranate, pineapple, and banana; based on the use of deep learning algorithms. Although the author used a large database, achieved high-performance accuracy, and reviewed the results of processing speed, he did not classify fruits of the same kind, and as we mentioned before, classifying fruits of the same type is much more difficult than classifying fruits of different types. The author did not compare the results of testing the accuracy of his proposed technique with the results of other techniques. The proposed model has succeeded in realizing a test accuracy of 98.9%. This paper is constructed as: in second section, overview of the methodology of the proposed technique is presented. Results and discussion are demonstrated in section three. In last section, conclusion and future lines are explained.

2. METHODOLOGY

The steps of the suggested method are included in this section. The suggested procedure starts with database collection, followed by data pre-processing (feature scaling, dataset augmentation, dataset splitting), CNN model construction, training, model validation, model testing, and hyper-parameter adjusting. Figure 1 shows the workflow of the CNN model we have suggested.

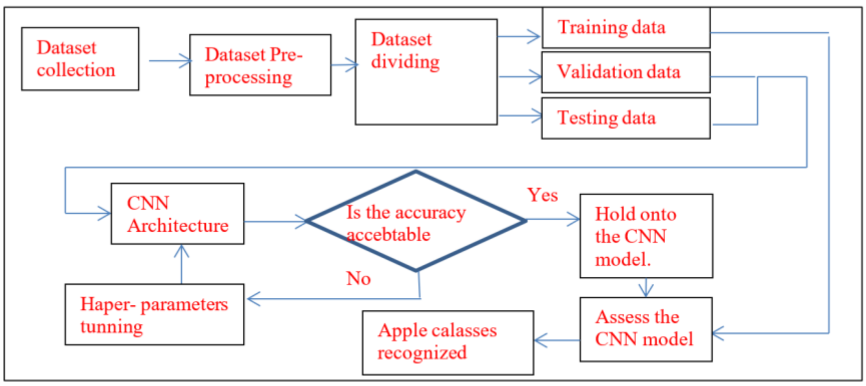


Figure 1. Workflow of our proposed CNN model

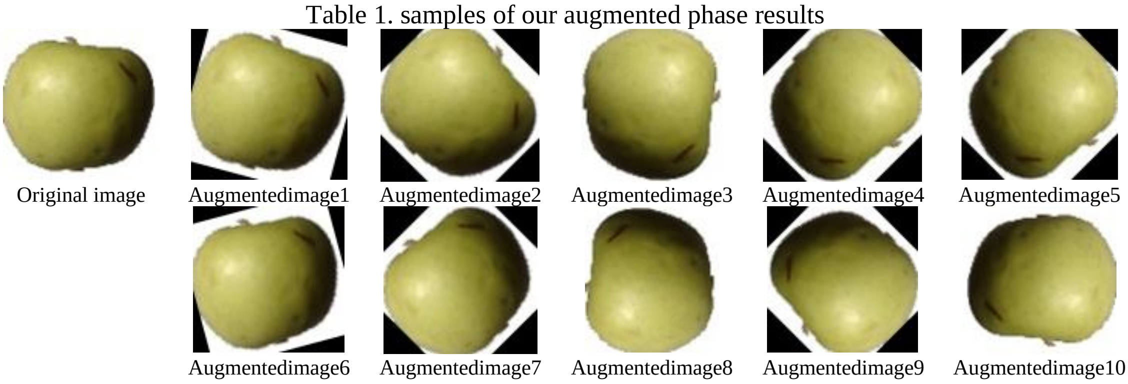
2.1. Dataset collection

In the proposed work, the dataset which is used is called fruits 360. This dataset includes more than 90380 excellent images of of 131 fruits and vegetables. 8,538 images of them are images for thirteen varieties of apple fruits, divided into 6,404 images for training work and 2,134 for test work. This dataset is available online for free at [33]. This number of images was duplicated ten times during the augmentation process, bringing the total number of images used in this study to 85,380 of images. These images were divided into 60% for training, 20% for validation, and 20% for testing.

2.2. Image pre-processing

The preliminary treatment of our proposal includes feature scaling, data augmentation, and data splitting. Feature scaling process in our case included the use of RGB formatted photos to scale our datasets into 128×128 dimensions. Additional to resizing the images, our feature scaling included also a normalization of the collected dataset. This is to o reduce the impact of illumination differences, additionally, the CNN ends faster when data is provided between [0, 1] than it does when data is provided between [0, 255]. The second phase of our proposal to pre-process the collected data is a data augmentation. The phrase "augmentation" describes the process of making the dataset larger. To prevent over-fitting, it is therefore utilized to increase the number of data samples and possibly the rate of variance in our dataset. In our case, all the collected data was rotated at ten different angles: -15, -45, -90, -135, -180, 15, 45, 90, 135, and 160. The samples of our augmented phase results are shown in Table 1. The outcomes of dataset augmentation phase are 85,380 of images. These dayaset of images were divided into 60% for training, 20% for validation, and 20% for testing.

Table 1. samples of our augmented phase results



2.3. Construction of our suggested convolutional neural network model

As shown in Figure 2, our suggested model (which is designed to categorize thirteen types of apple fruits) includes two convolutional layers, two max-pooling layers, one dropout layer, and a fully connected layer. 2 CNN layers were built, with the first convolutional layer (conv2D) being made up of 64 filters with a 3×3-pixel size. The second convolutional layer, which have the same number of filters and filter sizes as the first layer receive the output from the first layer. Following the convolutional layers, an activation function is applied to the output after the convolution procedure in order to accommodate non-linearity. In our proposel the rectified linear unit (ReLU) activation function has the role of activating the convent. Following the activation function is the sub-sampling layer, which employs maxpool and is 2×2 in size. Following the sub-sampling laye is the dropout layerr, which is a layer that is a regularization method for neural networks in which certain neurons are assigned at random and not used while retraining. Finally, there are two completely interwoven layers that discriminate between various apple classess, these dense layers are with 'softmax' activation function. For both conv layers, 64 kernel of spatial size 3×3 with stride size 1 and padding of 2 were used. For both pooling layers, max pool operation with kernel size 2×2, stride 2, and zero padding.

2.4. Hapyer-parameters tunning of our suggested convolutional neural network model

To make accurate predictions, various datasets need distinct sets of hyperparameters. The abundance of hyperparameters, however, makes it challenging for consumers to select one. The best number of neurons, the number of layers, or the optimizer that works best across all datasets cannot be determined. Finding the optimum potential sets of hyperparameters to construct the model from a given dataset requires adjusting hyperparameter. In general, the hyperparameters to tune the deep convenutional neural network are the number of neurons in each layer, activation function, optimizer model, drop-out rate, batch size, and epochs (number of iterations in training), the number of layers, kernel size in convolutional layers, pooling size. In our suggested CNN model, the following hyper-parameters were addressed using the validation set: 64 neurons in each laer, ReLU activation function, Adam optimizer,0.2 dropout rate, batch size at 16, epochs at 1, 6 layers, 3×3 CONV kernal size, 2×2, max-pooling kernal size, 2 stride size, and 1 amount of zero padding.

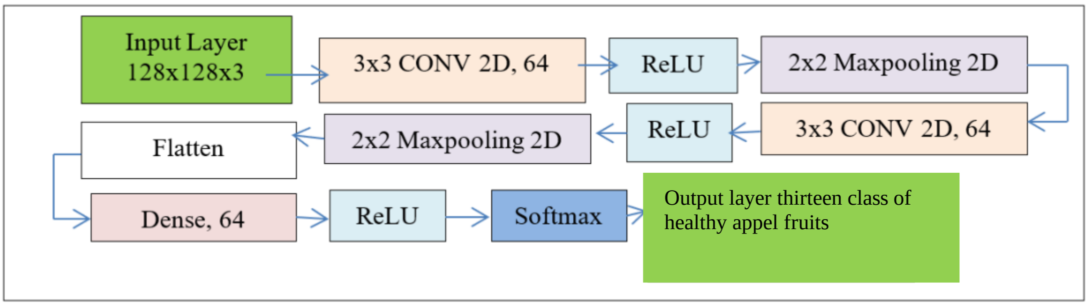


Figure 2. Architecture of our CNN mode

3. RESULTS AND DISCUSSION

Results and a discussion of the performance analysis of our suggested method are provided in this section. The training, validation, and testing results of the suggested approach for classifying thirteen distinct apple types are presented in an illustrated format. The outcomes of the suggested technique are contrasted with those of related techniques.

3.1. Training results of the suggested model

The proposed model was trained on 64,040 images for thirteen varieties of apple fruits distributed over thirteen folders. Various epochs counts were used in the suggested model (10 and 5). The training duration, training losses, and training accuracy of our suggested CNN model at 10 epochs and 5 epochs are displayed in Tables 2 and 3. It is evident from these data in the tables that the suggested model picks things up rapidly because, given the kind of epoch's counts, the training accuracy reaches 100% by the third epoch. It suggests that the proposed model is easily learnable, as it can fully learn to identify thirteen different apple classes starting from the third epoch. Furthermore, with this huge number of photos, it just took a few seconds to recognize the thirteen different sorts of apple fruits.

Table 2. Training results of our proposed CNN model at 10 counts of epochs

Epochs number	Batch size	Training time (s)	Training losses	Training accuracy
1/10	16	8.18	3.9520	0.7692
2/10	16	7.18	0.0023	0.9995
3/10	16	7.18	0.0023	0.9992
4/10	16	7.18	0.0066	1.00
5/10	16	7.17	0.0000	1.00
6/10	16	7.18	0.0000	1.00
7/10	16	7.17	0.0000	1.00
8/10	16	7.18	0.0000	1.00
9/10	16	7.17	0.0000	1.00
10/10	16	7.18	0.0000	1.00

Table 3. Training results of our proposed CNN model at 5 counts of epochs

Epochs number	Batch size	Training time (s)	Training losses	Training accuracy
1/5	16	8.18	3.8593	0.7701
2/5	16	7.18	0.0012	1.0000
3/5	16	7.18	0.0062	0.9981
4/5	16	7.18	0.0000	1.00
5/5	16	7.17	0.0000	1.00

3.2. Validation results of the suggested model

The proposed model was validated over 21,340 images for thirteen varieties of apple fruits distributed over thirteen folders. The results of the validation work for the proposed model appear in Table 4. These results include, as is the case for training work, validating time, validation losses, and validation accuracy. The results show the ability of the proposed method to fully identify all of these types of apple fruits after the fifth epoch. The results of performance accuracy, validation losses, and validating times are very similar to the training results of the proposed method.

Table 4. Training results of our proposed CNN model at 10 counts of epochs

Epochs number	Batch size	Validating time (s)	Validation model losses	Validation model accuracy
1	16	8.18	3.9520	76.92
2	16	7.18	1.0535	98.95
3	16	7.18	1.0323	98.92
4	16	7.18	0.0077	99.79
5	16	7.17	0.0023	99.82
6	16	7.18	0	100
7	16	7.17	0	100
8	16	7.18	0	100
9	16	7.17	0	100
10	16	7.18	0	100

3.3. Confusion matrix results for testing the proposed convolutional neural network model

Two statistical performance metrics for classification tests are sensitivity and precision. The capacity of the prediction model to choose an instance of a specific class from the dataset is referred to as sensitivity. The percentage of genuine affirmative classifications that are accurately identified is what matters. Contrarily, accuracy is defined as the percentage of accurately detected anticipated positive classes. They come from (1) and (2).

$$sensisitivity = \frac{TP}{(TP+FN)} \tag{1}$$

$$Precision = \frac{TP}{(TP+FP)} \tag{2}$$

The numbers for the true positive, false positive, and false negative forecasts for the class under consideration are, respectively, true positive, false positive, and false negative. The results of the suggested technique's confusion matrix (class sensitivity and class precision) for the thirteen different apple fruits are shown in Table 5. The findings indicate that:

- Eight varieties could be distinguished with 100% accuracy.
- A whopping 99% of cultivars have been identified.
- A class that was discovered at a 95% rate, followed by another class that was discovered at a 92.6% rate.
- The ninth grade received an accuracy score of 86%, which was the lowest performance accuracy achieved by the suggested technique.
- The proposed method's overall accuracy across the thirteen items was 98.9%.

Table 5. Confusion matrix for test accuracy of the proposed CNN model

Actual class	Predicted class													Class sensitivity %
	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	
Class 1	1520	120	0	0	0	0	0	0	0	0	0	0	0	92.6
Class 2	0	1480	0	0	0	0	0	0	0	0	0	0	0	100
Class 3	0	0	1600	0	0	0	0	0	0	0	0	0	0	100
Class 4	0	0	0	1640	0	0	0	0	0	0	0	0	0	100
Class 5	0	0	0	0	1540	70	0	0	0	0	0	0	0	95
Class 6	0	0	0	0	0	1640	0	0	0	0	0	0	0	100
Class 7	0	0	0	0	0	0	1520	0	0	0	0	0	0	100
Class 8	0	0	0	0	0	0	0	1630	0	1	0	0	0	99
Class 9	0	0	0	0	0	0	260	0	1390	0	0	0	0	86
Class 10	0	0	0	0	0	0	0	1	0	1430	0	0	0	99
Class 11	0	0	0	0	0	0	0	0	0	0	1660	0	0	100
Class 12	0	0	0	0	0	0	0	0	0	0	0	1640	0	100
Class 13	0	0	0	0	0	0	0	0	0	0	0	0	2190	100
Class precision %	100	92.5	100	100	100	96	85.5	99	100	99	100	100	100	Overall correctness = 98.9

3.4. Comparesion between the final test results of the suggested model and the related models

In this section, a comparison is presented between the results of testing the proposed classifier and the results of testing a group of transfer learning classifiers. The results of testing the proposed technique for identifying 13 types of apple fruits appear in Table 6. These results include test accuracy, recall and, f1-score, support, batch size, and epoch number. The results show the high accuracy of the proposed technique in identifying different types of apple fruits as best as possible, as the average accuracy of the proposed model in test for identifying thirteen different types of apple fruits reached 98.9%.

Table 6. Final test accuracy, recall, fa-score, support, batch size, epotch number of the proposed classifier

Epoch number	Batch size	Test accuracy (%)	Recall	F1-score	Support
10	16	98.9	1	1	166
5	16	98.9	1	1	166

On the other hand, Table 7 displays the test results of four of the best classifiers, which are VGG16, EfficientNetV2M, MobileNetV2, and InseptionV3 to identify only eight different types of apple fruits as mentioned in the research paper referred to in Cortés *et al.* [34]. These results include training time, test accuracy, recall, f1-score, and support, batch size, epoch number. The results show that the VGG16 classifier achieved an accuracy of 69.89%, the EfficientNetV2M classifier achieved an accuracy of 70.54%, the MobileNetV2 classifier achieved an accuracy of 91%, and finally the InseptionV3 classifier achieved an accuracy of 92.96%. The results also show that this accuracy was achieved after a number of epochs amounting to 100 epochs. The results also show that training times varied between one and four hours. Therefore, all of these results show the significant superiority in favor of the proposed classifier over the other classifiers in all directions, whether in the number of classes 13 versus 8, the performance accuracy is 98.9% in favor of the proposed versus 69.89% to 92.96%, training times 7.18 seconds versus between 1.23 hours to 4.02 hours, and finally epochs conts, as the proposal requires 3 to 5 epochs to fully identify the different types. In contrast, other techniques exceeded 100 epochs to achieve the obtained accuracy.

Table 7. Test accuracy, recall, f1-score, support, batch size, epotch number, and training time for different related algorithms

CNN architecture	Test accuracy (%)	Batch size	Epoch number	Recall	F1-score	Support	Training time
VGG 16	69.89	24	100	0.589	0.688	49	1:39h
EfficientNetV2M	70.54	24	100	0.725	0.675	46	4:02h
MobileNetV2	91	24	100	0.734	0.890	62	1:23h
InseptionV3	92.96	24	100	0.978	0.929	67	1:27h

4. CONCLUSION

Design and implementation of apple fruits classification system based on CNN algorithm is presented in this work. The designed model works to classify thirteen types of apple fruits with high accuracy and high processing speed. The proposed technique was based on training and testing the model on a maximum number of images of apple fruits, by increasing the number of database images tenfold, after augmentation was performed on the images. The technology also relied on good tuning of the hyperparameters. To further ensure the efficiency of training, validation was performed on 20% of the database. All results that demonstrate the high efficiency of the proposed model were reviewed. The results of the proposal were compared with the results of four related techniques. The results showed the great advantage of the proposed technology at all levels. In the proposed method 64040 images for model training were used, images belonging to 13 classes and 21340 images belonging to 13 classes for model validating and testing. The proposed model has succeeded in realizing a test accuracy of 98.9%. Future lines of this work will focus on the following: first, modify the proposed model to classify the type of apple, the apple fruit helthy or defected, and then the defect type for each one. Second, think about the hardware implementation of the technique that gives the best results (high accuracy in a very low time), so that it can be used in industrial enterprises that rely on computer vision techniques.

REFERENCES

[1] F. Femling, A. Olsson, and F. A. -Fernandez, "Fruit and vegetable identification using machine learning for retail applications," in *2018 14th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)*, Nov. 2018, pp. 9–15, doi: 10.1109/SITIS.2018.00013.

[2] A. A. Nashat and N. M. H. Hassan, "Automatic segmentation and classification of olive fruits batches based on discrete wavelet transform and visual perceptual texture features," *International Journal of Wavelets, Multiresolution and Information Processing*, vol. 16, no. 1, Jan. 2018, doi: 10.1142/S0219691318500030.

[3] N. M. H. Hassan and A. A. Nashat, "New effective techniques for automatic detection and classification of external olive fruits defects based on image processing techniques," *Multidimensional Systems and Signal Processing*, vol. 30, no. 2, pp. 571–589, Apr. 2019, doi: 10.1007/s11045-018-0573-5.

[4] K. Tan, W. S. Lee, H. Gan, and S. Wang, "Recognising blueberry fruit of different maturity using histogram oriented gradients and colour features in outdoor scenes," *Biosystems Engineering*, vol. 176, pp. 59–72, Dec. 2018, doi: 10.1016/j.biosystemseng.2018.08.011.

[5] S. Sabzi, Y. A. -Gilandeh, and G. G. -Mateos, "A new approach for visual identification of orange varieties using neural networks and metaheuristic algorithms," *Information Processing in Agriculture*, vol. 5, no. 1, pp. 162–172, Mar. 2018, doi: 10.1016/j.inpa.2017.09.002.

[6] A. Pande, M. Munot, R. Sreeemathy, and R. V. Bakare, "An efficient approach to fruit classification and grading using deep convolutional neural networ," in *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, Mar. 2019, pp. 1–7, doi: 10.1109/I2CT45611.2019.9033957.

[7] M. S. Hossain, M. Al-Hammadi, and G. Muhammad, "Automatic fruit classification using deep learning for industrial applications," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 2, pp. 1027–1034, Feb. 2019, doi: 10.1109/TII.2018.2875149.

[8] S. L. Raja, N. Ambika, V. Divya, and T. Kowsalya, "Fruit classification system using computer vision: a review," *International Journal of Trend in Research and Development*, vol. 5, no. 1, pp. 22–26, 2018.

[9] H. Mureşan and M. Oltean, "Fruit recognition from images using deep learning," *Acta Universitatis Sapientiae, Informatica, The Journal of Sapientia Hungarian University of Transylvania*, vol. 10, no. 1, pp. 26–42, Dec. 2018.

[10] N. M. H. Hassan, B. R. G. Elshoky, and A. M. M. Mabrouk, "Quality of performance evaluation of ten machine learning algorithms in classifying thirteen types of apple fruits," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 30, no. 1, pp. 102–109, Apr. 2023, doi: 10.11591/ijeecs.v30.i1.pp102-109.

[11] Z. M. Khaing, Y. Naung, and P. H. Htut, "Development of control system for fruit classification based on convolutional neural network," in *2018 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus)*, Jan. 2018, pp. 1805–1807, doi: 10.1109/EIConRus.2018.8317456.

[12] A. Nasiri, A. T. -Garavand, and Y.-D. Zhang, "Image-based deep learning automated sorting of date fruit," *Postharvest Biology and Technology*, vol. 153, no. 3, pp. 133–141, Jul. 2019, doi: 10.1016/j.postharvbio.2019.04.003.

[13] N. Ismail and O. A. Malik, "Real-time visual inspection system for grading fruits using computer vision and deep learning techniques," *Information Processing in Agriculture*, vol. 9, no. 1, pp. 24–37, Mar. 2022, doi: 10.1016/j.inpa.2021.01.005.

[14] S. Naik and B. Patel, "Machine vision based fruit classification and grading - A review," *International Journal of Computer Applications*, vol. 170, no. 9, pp. 22–34, Jul. 2017, doi: 10.5120/ijca2017914937.

[15] P. Moallem, A. Serajoddin, and H. Pourghassem, "Computer vision-based apple grading for golden delicious apples based on surface features," *Information Processing in Agriculture*, vol. 4, no. 1, pp. 33–40, Mar. 2017, doi: 10.1016/j.inpa.2016.10.003.

[16] J. L. R. -Aranda, J. I. N. -Varela, J. C. C. -Tello, and G. R. -Ramirez, "Fruit classification for retail stores using deep learning," in *MCPR 2020: Pattern Recognition*, 2020, pp. 3–13, doi: 10.1007/978-3-030-49076-8_1.

[17] A. Kader, S. Sharif, P. Bhowmick, F. H. Mim, and A. Y. Srizon, "Effective workflow for high-performance recognition of fruits using machine learning approaches," *International Research Journal of Engineering and Technology (IRJET)*, vol. 7, no. 2, pp. 1516–1521, 2020.

[18] L. S. P. Annabel, T. Annapoorani, and P. Deepalakshmi, "Machine learning for plant leaf disease detection and classification – A review," in *2019 International Conference on Communication and Signal Processing (ICCSP)*, Apr. 2019, pp. 0538–0542, doi: 10.1109/ICCSP.2019.8698004.

[19] A. Nosseir and S. E. A. Ahmed, "Automatic classification for fruits' types and identification of rotten ones using k-NN and SVM," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 15, no. 3, pp. 47–61, Feb. 2019, doi: 10.3991/ijoe.v15i03.9832.

[20] H. M. W. M. Hippola, D. P. W. Mesthri, R. M. T. P. Rajakaruna, L. Yasakethu, and M. Rajapaksha, "Machine learning based classification of ripening and decay stages of mango (*Mangifera indica L.*) cv. Tom EJC," in *2022 2nd International Conference on Image Processing and Robotics (ICIPRob)*, Mar. 2022, pp. 1–6, doi: 10.1109/ICIPRob54042.2022.9798722.

[21] D. G. Koç and M. Vatandaş, "Classification of some fruits using image processing and machine learning," *Turkish Journal of Agriculture - Food Science and Technology*, vol. 9, no. 12, pp. 2189–2196, Dec. 2021, doi: 10.24925/turjaf.v9i12.2189-2196.4445.

[22] A. A. A. El-aziz, A. Darwish, D. Oliva, and A. E. Hassanien, "Machine learning for apple fruit diseases classification system," in *AICV 2020: Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2020)*, 2020, pp. 16–25, doi: 10.1007/978-3-030-44289-7_2.

[23] K. Sabanci and M. F. Unlersen, "Different apple varieties classification using kNN and MLP algorithms," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 4, pp. 166–169, 2016.

[24] N. Chaithra, B. Madhu, K. Umamaheswari, and S. Balasubramanian, "Classification and regression tree (CART) algorithm for the prediction of ischemic heart disease," *International Journal of Future Generation Communication and Networking*, vol. 13, no. 4, pp. 196–206, 2020.

[25] A. Tharwat, T. Gaber, A. Ibrahim, and A. E. Hassanien, "Linear discriminant analysis: A detailed tutorial," *AI Communications*, vol. 30, no. 2, pp. 169–190, May 2017, doi: 10.3233/AIC-170729.

[26] S. Wang and Q. Chen, "The study of multiple classes boosting classification method based on local similarity," *Algorithms*, vol. 14, no. 2, Jan. 2021, doi: 10.3390/a14020037.

[27] D. A. McCarty, H. W. Kim, and H. K. Lee, "Evaluation of light gradient boosted machine learning technique in large scale land use and land cover classification," *Environments*, vol. 7, no. 10, Oct. 2020, doi: 10.3390/environments7100084.

[28] F. R. Lumbanraja, E. Fitri, Ardiansyah, A. Junaidi, and R. Prabowo, "Abstract classification using support vector machine algorithm (case study: Abstract in a computer science journal)," *Journal of Physics: Conference Series*, vol. 1751, no. 1, Jan. 2021, doi: 10.1088/1742-6596/1751/1/012042.

[29] S. Sakib, Z. Ashrafi, and M. A. B. Siddique, "Implementation of fruits recognition classifier using convolutional neural network algorithm for observation of accuracies for various hidden layers," *ArXiv e-Journal*, pp. 1-4, Apr. 2019.

[30] F. M. A. Mazen and A. A. Nashat, "Ripeness classification of bananas using an artificial neural network," *Arabian Journal for Science and Engineering*, vol. 44, no. 8, pp. 6901–6910, Aug. 2019, doi: 10.1007/s13369-018-03695-5.

[31] F. Risdin, P. K. Mondal, and K. M. Hassan, "Convolutional neural networks (CNN) for detecting fruit information using machine learning techniques," *IOSR Journal of Computer Engineering (IOSR-JCE)*, vol. 22, no. 2, pp. 01–13, 2020.

[32] M. Yang and S. I. Cho, "Fruit classification using convolutional neural network (CNN)," *Precision Agriculture Science and Technology*, vol. 3, no. 1, pp. 1–8, 2021, doi: 10.12972/pastj.20210001.
[33] M. Oltean, "Fruits-360 dataset," *Kaggle*, 2021. [Online]. Available: https://www.kaggle.com/datasets/moltean/fruits
[34] S. G. Cortés, A. M. Díaz, J. A. O. Prendes, and A. B.García, "Transfer learning with convolutional neural networks for cider apple varieties classification," *Agronomy*, vol. 12, no. 11, Nov. 2022, doi: 10.3390/agronomy12112856.

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