



PRIMARY RESEARCH

Evaluating fruit grading techniques: A comprehensive review of image processing approaches

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Keywords

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Abstract

Abstract — Fruit quality, including color, texture, size, and defects, significantly influences their market value and customer preference. Conventional manual fruit quality assessment methods are both time-consuming and labor-intensive. Image processing methods, particularly convolutional neural networks (CNNs), have proven to be efficient in automating fruit quality recognition to address this issue. This study compares various CNN models' accuracy in classifying images of fresh and rotten apples, bananas, and oranges. We assessed three pre-trained CNN models—MobileNet V2, ResNet50, and VGG19—alongside the K-Nearest Neighbors (KNN) algorithm. The findings suggest that VGG19 achieved the highest accuracy at 99.56%, followed by MobileNet V2 at 98.37%, and ResNet50 at 94.21%. The accuracy of the KNN algorithm, however, was notably lower at 68.18%. This study sheds light on the effectiveness of different CNN models for assessing fruit quality and offers direction for future research in fruit image classification.

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I. INTRODUCTION

Each country's horticultural industry is significant to its financial development. Pakistan is one of the world's top producers of a wide range of agricultural goods, according to the Food and Agriculture Organization (FAO). For a number of important products, including wheat, cotton, sugarcane, mangoes, dates, and oranges, the nation is among the top ten producers in the world. Remarkably, rice, a fundamental food crop essential to both local and international trade, is produced in Pakistan in the tenth-largest amount [1]. By the end of 2023, Pakistan's agriculture sector is expected to contribute significantly to the country's economy. More specifically, it is anticipated that agriculture will contribute roughly 9,143,105 million Pakistani Rupees (PKR) to the GDP. Macroeconomic models and professional assessments from Trading Economics and other economic fore-

casting organizations serve as the foundation for this prediction. [2] The sector has a vital part in Pakistan's economy, as seen by its expansion, which also shows how important it is to the livelihoods of millions of Pakistanis.

Farming comprises the biggest area of our economy. Larger part of the populace, straightforwardly or by implication, subject to this area. Our brains are generally able to analyze our vision. It requires little effort on the part of our brain to understand and read a sign, distinguish between a tiger and a leopard, or identify people by their faces. Everything here is too basic for people. However, for computers, these are the real challenges to overcome. Systems that grasp what we are looking at and what actions we need to do may now be developed. thanks to advancements that image processing algorithms can analyze images. Fruit grading is an essential part in the agriculture sector due to the mar-

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ket's significant demands worth after being inspected, evaluated, and sorted. Fruits are graded and sorted by hand during the process of fruit grading. Fruits may be sorted by size, shape, and quality using machinery when they are being graded. Fruits graded by human eye can sometimes cause errors in grading quality while working with a large amount of fruits. Fruit quality grading by image processing may offer significant advantages and versatility. Fruits' image processing reduces inaccuracy while simultaneously advancing processing time. Fruits are in high demand in both domestic and international markets. The fruits must be handled carefully during grading since they are quite sensitive. The image processing methodology is fast, dependable, and objective for fruit inspection, and the industry has embraced it. Fruit grading has relied more and more on cutting-edge image processing techniques in recent years to increase efficiency and accuracy. The shortcomings and inefficiencies of manual grading led to this technological change. In the past, human inspectors evaluated each fruit piece for a variety of quality factors, such as size, color, and the existence of flaws or illnesses. But in addition to being labor-intensive, this manual procedure is also prone to human error and inconsistency. Sophisticated algorithms and high-resolution cameras are used in modern image processing systems to assess fruits more accurately. These systems take close-up pictures of every fruit and then classify and identify flaws like blemishes, malformations, and bruises. They also evaluate the extent of any potential ailments, such as rot or fungal infections. When compared to human inspection, our automated grading procedure guarantees a more consistent and impartial evaluation. So many fruit grading systems have been created using image processing methods with deep learning models or machine learning algorithms. The fundamental steps of the fruit grading based on image processing are image acquisition, image segmentation, feature extraction, Comparison and decision-making based on data. This study compares some effective image processing algorithms and CNN models for grading fruits in order to assess their comparative effectiveness.

II. FRUIT GRADING PROCESS THROUGH IMAGE CLASSIFICATION

A number of crucial steps are involved in the image processing-based fruit grading process, all of which contribute to the precise and effective assessment of fruit quality. First, high-resolution photographs of the fruits are taken using specialized cameras or imaging systems during the image acquisition and pre-processing stage. The pre-processing stage then improves the photos by utiliz-

ing methods such as histogram equalization and filtering to increase contrast and clarity, as well as modifying lighting, color correction, and noise reduction.

The next step is feature extraction, which involves quantifying particular fruit features. Measuring characteristics including size, shape, color, texture, and the existence of flaws or illnesses is part of this. Measurable data is created from the visual information, which is essential for additional analysis. For instance, color analysis evaluates ripeness and maturity, whereas texture analysis assists in locating surface flaws.

Following their extraction, the features are compared to predetermined standards or reference datasets using data-based contrast analysis. This study aids in the differentiation of various quality grades, such as grade A or premium, according to the kind and degree of flaws or illnesses found.

A. Image Acquisition and Preprocessing

Images of fruits can be obtained from primary sources such as to capture them with a camera or secondary sources can be used such as acquiring data from already developed datasets from different sources. To adjust the brightness value in an output image, preprocessing techniques employ a method known as filtration, which involves examining a small, localized area surrounding each pixel in the input image. This approach allows for precise modifications to the image based on its immediate context. Local preprocessing approaches are often classified into two primary kinds, depending on their intended function. The first type focuses on smoothing out image noise and slight differences. This method can assist in producing a result that is cleaner and more visually consistent by minimizing high-frequency events in the image. Random noise and minor irregularities are lessened by this approach, which averages the pixel values within the surrounding area. But this smoothing process comes with a cost. It may aid in the suppression of noise and small changes, but it may also result in the image losing some crucial features. Edges and limits, which are essential for identifying minute details and preserving the image's overall clarity, may become blurry as a result of the smoothing effect. As a result, even though the image looks cleaner, important details could become less distinct or even invisible. The foundation of gradient operators is a local component of the input image. In areas of the image where the picture function varies quickly, derivatives are bigger. Such areas in the image are what the gradient operators are intended to show. In the frequency domain, gradient operators reduce low frequencies

B. Image Segmentation

Image segmentation is essential for effectively categorizing and sorting fruit according to its visual qualities in fruit grading. Using this technique, digital photographs of fruit are divided into discrete segments or regions that correlate to various characteristics like color, size, and surface flaws. In this case, the main objective of image segmentation is to streamline the picture representation in order to facilitate the analysis and assessment of the fruit's quality. Fruit grading techniques include thresholding, which uses color intensity to help distinguish ripe from unripe fruits; edge detection, which uses the fruit's contours to measure size and shape; and region-based techniques, which divide the fruit's surface into sections to look for flaws like bruises or blemishes. Utilizing image segmentation techniques in fruit grading improves sorting fruit for commercial sale's accuracy and efficiency while guaranteeing that buyers only purchase high-quality food. Notwithstanding its benefits, the method is not without problems. For example, different lighting conditions and fruit looks can have an impact on the accuracy of segmentation. Metrics like accuracy, precision, and recall are used to assess performance in order to make sure that the grading system can consistently discriminate between fruit varieties with varying quality levels [3]. Methods for segmenting images are grouped according to two characteristics: discontinuity and resemblance. One of the most important steps in fruit grading is image segmentation, which is separating individual fruits using their visual attributes from both their backdrop and from one other. The goal of boundary-based segmentation techniques is to locate and examine image discontinuities. By identifying edges or borders where color or texture abruptly changes, this technique enables the system to accurately define each fruit's features. For instance, it can tell an apple's smooth surface apart from the surrounding area or tell fruits apart if they are grouped together. On the other hand, region-based techniques depend on how comparable the pixel values are within specific regions of the picture. These methods assist identify and classify various fruits based on shared properties by grouping pixels with comparable characteristics, such color or texture. A region-based method, for example, might identify all pixels falling inside a specific color range as either suggestive of a specific ripeness level or as belonging to a specific fruit kind.

C. Feature Extraction

A simple form of image processing is feature extraction. The important part is the feature of an image. The word feature is frequently used in pattern recognition to refer to the

particular descriptors that identify and distinguish different objects within a picture. The process of extracting visual characteristics that define the fruits comes after an image has been segmented, which separates the areas of interest. This entails recognizing and evaluating characteristics like size, texture, color, and shape. To distinguish different fruit varieties and their maturity levels, for example, color feature extraction entails evaluating the dominant hues and color distribution among the divided fruit sections. Fruit dimensions are measured by size feature extraction, which provides crucial information for size-based sorting and classification. Shape feature extraction looks at the fruits' geometric characteristics and curves to identify flaws and differentiate between types. To improve object recognition and classification accuracy, a range of visual descriptors and local feature detectors are also used. Together, these techniques allow for an accurate and thorough description of every fruit, which makes sorting and grading procedures more efficient. The most visually compelling aspect of any image is its colour, which is crucial for classification, grading, and differentiating faulty from healthy produce. The majority of the systems in use today determine a fruit's maturity by contrasting its colour with a set of established reference colours. Methods for extracting colour features are frequently utilised in agricultural applications, particularly in the grading and classification of fruits. Date fruit maturity and quality are assessed using back projection and 2D colour histograms to determine co-occurrence frequency in [4]. For fruit disease detection and fruit grading, a review of several segmentation approaches, colour models, and feature extraction strategies are included in [5]. Mango fruit sorting done in [6] Classifying fruits based on color and texture features within a class is done in [7] ANN achieving 83-98% accuracy in presents a method of recognizing fruit using color and texture features.

D. Data Based Contrast, And Decisive Procedures

The predefined classification and sorting criteria are compared with the features that were collected from the image. Based on the features identified, comparison is performed. The fruits are classified and graded. Machine learning algorithms can be used to compare information and make decisions based on that information. Some of the machine learning algorithms and CNN models are K-nearest neighbor (KNN), VGG-19, Resnet 50, MobilenetV2. Some algorithms are explained below in method section. Classification and grading procedure ends with this stage. Therefore, the fruit classification and grading procedure includes all of the steps listed above.

III. LITERATURE REVIEW

One of the most essential and important processes that follows harvesting is the sorting of agricultural products according to the product quality. This practice makes it easier for customers to judge a product's quality and promotes a more coordinated supply and distribution of agricultural goods. Quality control in the food industry was previously handled by professionals. It is obvious that traditional methods perform poorly and are expensive and ineffective when trying to meet rising customer demands. Modern technology like image processing has advanced significantly, both theoretically as well as practically. These techniques have recently benefited the food business, and their application has allowed for successful inspection of food goods. Sorting is the process of grouping items into uniform and standardized classes. This procedure is one of the most significant uses of an image processing approach that separates items or products on their apparent physical characteristics. [8] Quality control by customers highly depends on the shape of a fruit.

Several studies have been conducted in the area of categorizing and sorting goods like kiwi fruit [9], strawberry [10], pear [11], tomato [12], apple [13] using image processing technique. Fruit image processing has been used extensively to identify flaws in fruit's size, shape, and appearance. Based on the shape of their external deformities, Riquelme, Barreiro, Ruiz-Altisent, and Valero organised olive fruits according to their defects. The fruits were initially categorized by experts into seven groups, and then those groupings were further subdivided into groups according to features including color and the shape of any outward anomalies. Liming and Yanchoo [14] created a system that sorts strawberries using images. The system recognized the physical attributes of strawberries by using the imaging features. According to their study, the sorting precision was 90% for shape features and 88.8% for colour features. Mousavi Balestani [15] utilized image analysis, cherry fruits were distinguished and classified according to fruit size, maturity, and defects. Their results showed that sorting by size, ripeness, and flaws could be done with 96%, 92%, and 90% accuracy rates, respectively. Kheiralipour and Pormah [16] used artificial neural networks and image processing to sort cucumber fruits, and it was shown that neural networks had the best sorting model with an accuracy of 97.1%.

Literature review on the subject shows that there is a need to identify the comparative study about the accuracy results between different image processing techniques so that most effective technique can be identified.

IV. RESEARCH METHODOLOGY

Convolutional neural networks, or CNNs, have emerged as the state-of-the-art technique for classifying images in recent years. Artificial neural networks, or CNNs, are used to process and analyze data, particularly image data. In this paper, we will be using a quantitative methodology to check the accuracy rate of some CNN models for image processing. We will be testing the models on a dataset of fruit images and measuring the percentage of images that are correctly classified by each model. Based on the results, we will discuss the implications of using CNNs for image processing and classification. In the fields of computer vision and machine learning, fruit image categorization is a highly contentious and significant research area. In this paper, It is aimed to identify the high accuracy providing machine learning algorithm or cnn model for image classification of fruits. This argument is supported by conducting a review of the literature and by discussing the results of various studies. It will also be discussed that the possible results of some of the known cnn models used for image classification on the dataset of fruits.

I have tested the accuracies of three CNN pre-trained models for fruit quality grading for 3 different fruit; apple, banana, orange on their different states; rotten and fresh. Along with that I also tested accuracy for quality grading of these fruits on a machine learning algorithm KNN as well. The test accuracy results are given below.

```
In [90]: neigh = KNeighborsClassifier(n_neighbors=2)
neigh.fit(X_train, y_train)
print("Test Accuracy: "+str(neigh.score(X_test, y_test)))

classifier = KNeighborsClassifier()
classifier.train(X_train, y_train)
dist = classifier.compute_distances_np(X_test)
y_test_pred = classifier.predict_labels(dist, k=2)
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
print("With k = 2 Got %d / %d correct -- accuracy: %f" % (num_correct, num_test, accuracy))

Test Accuracy: 0.681943714023691
With k = 2 Got 744 / 1091 correct -- accuracy: 0.681943
```

Fig. 1. KNN results

```
Epoch 1/5
341/341 [=====] -- 69s 193ms/step -- loss: 0.1171 -- accuracy: 0.9690 -- val_loss: 0.9561 -- val_accuracy: 0.9796
Epoch 2/5
341/341 [=====] -- 63s 183ms/step -- loss: 0.4033 -- accuracy: 0.9911 -- val_loss: 0.4021 -- val_accuracy: 0.9930
Epoch 3/5
341/341 [=====] -- 66s 193ms/step -- loss: 0.4150 -- accuracy: 0.9952 -- val_loss: 0.4126 -- val_accuracy: 0.9941
Epoch 4/5
341/341 [=====] -- 69s 203ms/step -- loss: 0.4060 -- accuracy: 0.9983 -- val_loss: 0.4042 -- val_accuracy: 0.9952
Epoch 5/5
341/341 [=====] -- 72s 213ms/step -- loss: 0.4100 -- accuracy: 0.9989 -- val_loss: 0.4073 -- val_accuracy: 0.9937
```

Fig. 2. MobileNetV2 results

```

Epoch 1/5
348/348 [=====] - 495 2s/step - loss: 17.3440 - accuracy: 0.4928 - val_loss: 1.7559 - val_accuracy: 0.8424
Epoch 2/5
348/348 [=====] - 747s 2s/step - loss: 0.7226 - accuracy: 0.8049 - val_loss: 0.4070 - val_accuracy: 0.8620
Epoch 3/5
348/348 [=====] - 706s 2s/step - loss: 0.3127 - accuracy: 0.8978 - val_loss: 0.4370 - val_accuracy: 0.8789
Epoch 4/5
348/348 [=====] - 731s 2s/step - loss: 0.1970 - accuracy: 0.9335 - val_loss: 0.3322 - val_accuracy: 0.9499
Epoch 5/5
348/348 [=====] - 716s 2s/step - loss: 0.1341 - accuracy: 0.9535 - val_loss: 0.1627 - val_accuracy: 0.9421
Out[19]: <tensorflow.python.keras.callbacks.History at 0x17587214b>

```

Fig. 3. ResNet50 results

```

In [17]: model.fit(train_loader, validation_data=val_loader,
348/348 [=====] - 1849s 3s/step - loss: 0.2799 - accuracy: 0.9099 - val_loss: 0.4020 - val_accuracy: 0.8689
Epoch 2/5
348/348 [=====] - 1189s 3s/step - loss: 0.4082 - accuracy: 0.8984 - val_loss: 0.4028 - val_accuracy: 0.9027
Epoch 3/5
348/348 [=====] - 1026s 4s/step - loss: 0.4132 - accuracy: 0.9068 - val_loss: 0.4096 - val_accuracy: 0.9088
Epoch 4/5
348/348 [=====] - 956s 3s/step - loss: 0.4085 - accuracy: 0.9177 - val_loss: 0.4093 - val_accuracy: 0.9092
Epoch 5/5
348/348 [=====] - 1079s 3s/step - loss: 0.4081 - accuracy: 0.9099 - val_loss: 0.4132 - val_accuracy: 0.9056
Out[17]: <tensorflow.python.keras.callbacks.History at 0x1842d87eb>

```

Fig. 4. VGG-19 results

TABLE 1
OVERALL COMPARISON OF ACCURACIES

Model name	Test accuracy
knn	68.18%
Mobilenet v2 pretrained model	98.37%
Resnet50 pretrained model	94.21%
VGG 19 pretrained model	99.56%

V. CONCLUSION

Fruits' external features such as color, size, shape and texture are essential for classification and grading. Advances in image processing technology and low-cost hardware and software have made automated image processing systems a great alternative to manual fruit classification and grading. Automated systems offer accurate, rapid, objective, and efficient results - making them a better choice for most tasks. This paper examines the steps involved in fruit classification and grading. Some pre trained CNN models and a machine learning approach like MobileNetV2, ResNet50, VGG 19, KNN has also been tested for fruit classification. Despite some challenges, image processing is set to revolutionize the way we safely test and analyze fruit classification and grading. In the future, image classification can be done on classifying and grading more fruits and vegetables. As image processing technique is revolutionizing day by day these techniques can also be used for identifying flowers, leaves and if a proper system is designed and adopts the image processing through machine learning or CNN models it can also be used for classifying plants through disease detection. For future work one can work on these techniques and develop a mobile application to help farmers and general public for identifying, categorizing and simply grading of fruits and vegetables.

REFERENCES

- [1] Pakistan at a Glance . (2028) | FAO in Pakistan | Food and Agriculture Organization of the United Nations," Fao.org, 2018. . [Online]. Available: <https://shorturl.at/e4IAa>
- [2] Trading Economics. (2023) Pakistan GDP from agriculture. [Online]. Available: <https://shorturl.at/tZFeN>
- [3] R. C. Gonzalez. (2018) Digital image processing. [Online]. Available: <https://shorturl.at/RReMg>
- [4] D. Zhang, D.-J. Lee, B. J. Tippetts, and K. D. Lillywhite, "Date maturity and quality evaluation using color distribution analysis and back projection," *Journal of Food Engineering*, vol. 131, pp. 161-169, 2014.
- [5] U. Solanki, U. K. Jaliya, and D. G. Thakore, "A survey on detection of disease and fruit grading," *International Journal of Innovative and Emerging Research in Engineering*, vol. 2, no. 2, pp. 109-114, 2015.
- [6] C. Nandi, B. Tudu, and C. Koley, "Machine vision based techniques for automatic mango fruit sorting and grading based on maturity level and size," *Sensing technology: current status and future trends II*, vol. 23, pp. 27-46, 2014.
- [7] S. Jana and R. Parekh, "Intra-class recognition of fruits using color and texture features with neural classifiers," *International Journal of Computer Applications*, vol. 148, no. 11, pp. 1-6, 2016.
- [8] A. Jahanbakhshi and K. Kheiralipour, "Evaluation of image processing technique and discriminant analysis methods in postharvest processing of carrot fruit," *Food Science & Nutrition*, vol. 8, no. 7, pp. 3346-3352, 2020. doi: 10.1002/fsn3.1614
- [9] M. H. Bahri, M. Rashidi, and R. Farahmandfar, "Kiwifruit shape classification based on geometrical attributes analysis," *Agricultural Engineering Research Journal*, vol. 7, no. 1, pp. 01-05, 2017.
- [10] X. Liming and Z. Yanchao, "Automated strawberry grading system based on image processing," *Computers and electronics in agriculture*, vol. 71, pp. S32-S39, 2010. doi: 10.1016/j.compag.2009.09.013
- [11] A. Alipasandi, H. Ghaffari, and S. Z. Alibeyglu, "Classification of three varieties of peach fruit using artificial neural network assisted with image processing techniques." 2013.

- [12] S. Laykin, V. Alchanatis, E. Fallik, and Y. Edan, "Image--processing algorithms for tomato classification," *Transactions of the ASAE*, vol. 45, no. 3, p. 851, 2002.
- [13] G. Vivek Venkatesh, S. M. Iqbal, A. Gopal, and D. Ganesan, "Estimation of volume and mass of axi-symmetric fruits using image processing technique," *International journal of food properties*, vol. 18, no. 3, pp. 608-626, 2015.
- [14] L. M. Oo and N. Z. Aung, "A simple and efficient method for automatic strawberry shape and size estimation and classification," *Biosystems Engineering*, vol. 170, pp. 96-107, 2018.
- [15] A. M. Balestani, P. Moghaddam, A. Motlaq, and H. Dolaty, "Sorting and grading of cherries on the basis of ripeness, size and defects by using image processing techniques." 2012.
- [16] K. Kheiralipour and A. Pormah, "Introducing new shape features for classification of cucumber fruit based on image processing technique and artificial neural networks," *Journal of Food Process Engineering*, vol. 40, no. 6, p. e12558, 2017.