JAMCM Journal of Applied Mathematics and Computational Mechanics 2024, 23(3), 7-18
www.amcm.pcz.pl p-ISSN 2299-9965
DOI: 10.17512/jamcm.2024.3.01 e-ISSN 2353-0588

FRUIT CLASSIFICATION BY ASSESSING SLICE HARDNESS BASED ON RGB IMAGING. CASE STUDY: APPLE SLICES

***Bashar S. Falih*[1], *Łukasz Gierz*[2], *Mustafa A.J. Al-Sammarraie*[3]**

[1] *Department of Electrical and Electronics Engineering, Çukurova University, Adana, Türkiye*
[2] *Institute of Machine Design, Poznan University of Technology, Poznań, Poland*
[3] *College of Agricultural Engineering Sciences, University of Baghdad, Baghdad, Iraq*
bashar92Eng@gmail.com, lukasz.gierz@put.poznan.pl, mustafa.ahm@coagri.uobaghdad.edu.iq

Received: 5 July 2024; Accepted: 10 September 2024

Abstract. Correct grading of apple slices can help ensure quality and improve the marketability of the final product, which can impact the overall development of the apple slice industry post-harvest. The study intends to employ the convolutional neural network (CNN) architectures of ResNet-18 and DenseNet-201 and classical machine learning (ML) classifiers such as Wide Neural Networks (WNN), Naïve Bayes (NB), and two kernels of support vector machines (SVM) to classify apple slices into different hardness classes based on their RGB values. Our research data showed that the DenseNet-201 features classified by the SVM-Cubic kernel had the highest accuracy and lowest standard deviation (SD) among all the methods we tested, at 89.51 % ± 1.66 %. This classifier has proved to be the best compared to the others with two features, DenseNet-201 and ResNet-18, along with WNN, NB, and SVM (cubic and linear) kernels.

MSC 2010: *68T45, 68U10, 65G20*
Keywords: *apple slice, hardness, quality, machine learning, convolutional neural network*

I. Introduction

Rapid classification of fruits in agricultural warehouses based on durability traits is becoming increasingly important, especially immediately after harvest [1]. Apple quality is the main factor determining their price, as it encompasses both external and internal characteristics [2]. Classifying fruits according to their characteristics enhances their market value, reduces losses, and thus increases their price [3]. Apples are classified most frequently based on morphological criteria, including color, shape, size, texture, and firmness [4]. Measurement of firmness is crucial to ensure the quality of apples and their marketability after harvest. Firmness is an indicator of maturity and quality, which affects storage period, durability, and consumer acceptance. Firmer fruits can be stored for longer times than softer fruits [5]. Quality assessment is an important part of fruit processing as it directly affects the economic benefits for farmers. When sorting and evaluating the quality of crops, it is not easy to distinguish between fruit quality levels. The manual evaluation process requires a lot of work. On the other hand, the manual sorting process causes improper sorting of the fruits. In recent years, image processing, computer vision, and deep learning have provided a sufficient, harmless, automated, and conclusive way to evaluate fruit quality instead of traditional classification methods [6]. Recent achievements in deep learning, especially in the field of computer vision, have led to improved classification accuracy. This method is more efficient, as it provides an automated image-based screening analysis. Machine vision-based image classification methods are gaining popularity because of their high effectiveness. Usually, the machine learning (ML) technique extracts image feature metrics for classification. These steps are involved in image preprocessing, feature extraction, classification model development, and validation [7]. Convolutional neural networks (CNNs) are a type of artificial neural network that employ convolutional operations at least in one of their layers [8]. In agriculture, CNN-based approaches have been used in fruit classification [9] and fruit detection [10]. Many studies have confirmed the effectiveness of CNN models in exactly recognizing fruits as fresh or spoiled, with a classification accuracy of 99 % [11]. Studies of CNN-based models have shown that they outperform traditional methods such as Support Vector Machine (SVM) and Multilayer Perceptron (MLP) in fruit classification tasks [12]. A CNN model was applied to detect mangosteen flaws with 97 % precision [13]. Grape cluster detection is possible using the combination of ML and image processing techniques [14]. A rapid, robust, and calibrated technique for counting wine grapes has been developed to facilitate yield [15]. Another study was conducted on the k-means technique to perform segmentation tasks on RGB images, classifying stem, leaves, background, and grape branches [16]. The aim of this work is to develop a neural network based on RGB values that classify apple slices into three groups: hard, medium and soft. The following methods would be used: thresholding methods to separate the apple slice from the background, then the background cropping method. The segmented apple slice is fed into the CNN model, which consists of the ResNet-18 and DenseNet-201 architectures to extract deep features. These extracted features are then used in different classifiers of ML, such as the SVM with both Cubic and linear kernels, Deep Neural Networks, and Naive Bayes (NB) for classification. It could be a very useful tool for scientists and apple growers who seek a way to test hardness levels at three different levels. The proposed approach has been verified in previous studies, as it has been proven to be effective in classifying various domains [17].

2. Materials

2.1. Sample preparation

The study was carried out using apple fruits randomly sampled from local markets in Baghdad, Iraq. The apples were cut into slices using a slicer. The thickness of the slices was 10 mm and the diameter of the slice ranged from 60 to 70 mm. The average hardness of these slices was 5.11 kgf/cm^2. A Chinese-made mini fruit hardness meter, model GY-M15, with an accuracy of ±2 %, was used to measure the hardness of apple slices. The measurement range ranges from 0.2 to 15 kgf/cm^2, The pressure head diameter reaches Φ11.1 mm. After slicing the apples, the apple slices were stored for five days in the refrigerator at 5 °C and 60 % humidity. The hardness was calculated, and photographs of the apple slices were taken every day of storage to obtain different hardness levels and RGB values.

2.2. Image acquisition

The stylized box was adapted as a chamber that allowed the maintenance of a constant environment (constant conditions) as shown in Figure 1. Photos were taken with an iPhone 12 camera.

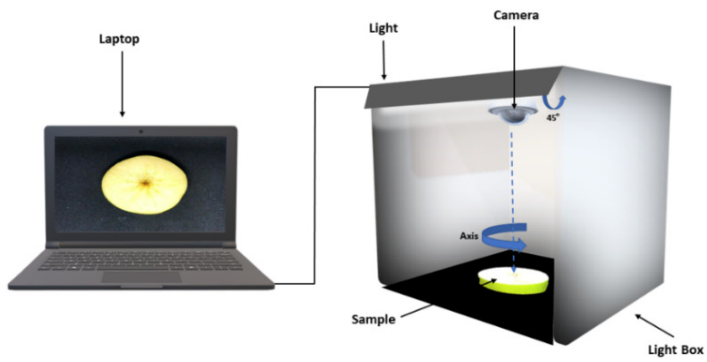

Fig. 1. Image capture system for apple slices

The distance between the apple slices and the camera was 20 cm. The intensity of illumination inside the photographic box was 200 lux via a lighting strip installed at an angle of 45 degrees perpendicular to the samples. This illumination angle reduces reflection, thus avoiding unwanted glare [18]. Each of the selected samples was processed by taking four photos of the above.

a) b) c)

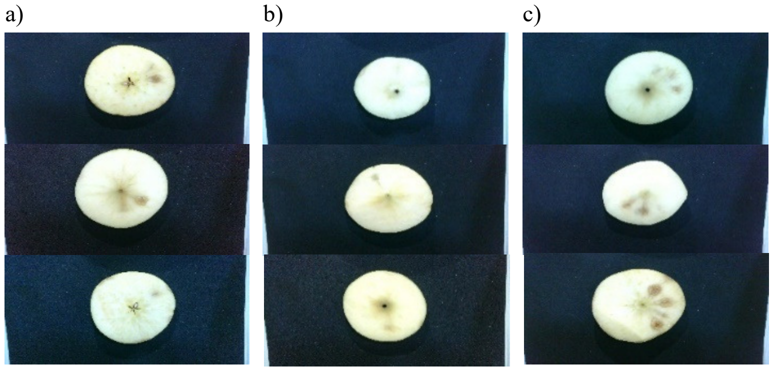
Fig. 2. Data sets examples of three levels of hardness used: a) low hardness, b) medium hardness, and c) high hardness

The data set encompasses three classes: Low, Medium, and High apple hardness, with each class comprising 400, 318, and 303 images, respectively. The images are full-color (RGB) and were the size of 1280×960×3 pixels. Data augmentation techniques involved rotating each image by angles of (π/4, π/2, π, and 3π/2), thus generating three to four images from each original image. Figure 2 shows examples of the 3 levels of apple hardness.

3. Method

Before apple slice hardness detection, all input images require preprocessing to ensure accuracy. Addressing key challenges in apple slice identification is paramount, including variations in image size and apple quality, fluctuations in illumination levels, and the processing of a large volume of images. Thus, the implementation of preprocessing stages for image enhancement and segmentation masks to distinguish the apple slice from the background is crucial. This paper's preprocessing stage encompasses color conversion, image segmentation, resizing techniques, feature extraction, and classifications, as displayed in Figure 3.

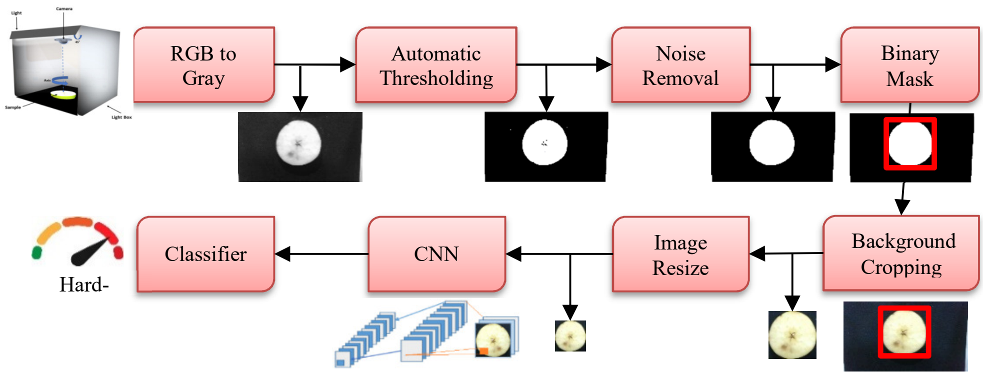

Fig. 3. Measurement methodology diagram

3.1. Preprocessing

To ensure accurate detection of the apple slice against the background, several steps are necessary. First, the image must be converted from RGB to grayscale, followed by the application of automatic thresholding, specifically Otsu's method. We used the improved 2D Otsu thresholding algorithm for image segmentation. Mathematical morphological operators, such as image opening, are then used to extract regions occupied by objects in the image. This procedure is a mixture of erosion and dilation [19]. A structural element is used to probe the image. Through image opening initially, the noise components are removed from the image, and the image is improved. This step helps to separate the apple slice from the background. The next step is to remove the noisy pixels by applying an opening operation with a 12×12 square 'disk' matrix. Finally, the maximum area of connected components is selected as a binary image mask, which enables one to exactly outline the apple slice.

3.2. Deep feature extractors (Convolution Neural Network (CNN))

CNNs, which are widely known for their automatic extraction of features from raw input images, can recognize very complex patterns with great precision [20]. In this study, DenseNet-201 and ResNet-18 were used as deep feature extractors. The DenseNet-201 network has a total of 708 layers, while ResNet-18 has 71 layers. Both networks have fully connected (fc) layers denoted as fc1000 and feature lengths of 1000. The input size of the images for both networks was set to 224×224×3. The features produced by these CNNs are then given to the ML classifiers to classify the three levels of hardness.

3.3. Classifiers

Three main supervised ML classifiers were used in the experiments.

Naïve Bayes (NB) classifier is an ML algorithm based on the Bayes Theorem. The NB class is an ML algorithm based on Bayes' Theorem. This model assumes that the data attributes are independent. That is why it is called "naïve". However, this simplification does not prevent the use of this method in many practical applications because of its simplicity, efficiency, and effectiveness. It is particularly useful for text classification tasks such as spam filtering and sentiment analysis, but it can also be used for other data processing applications [21]. For the naïve Bayes method, the following assumption must be satisfactory: Let $x = \{x_1, \dots, x_k\}$ be an instance of the example, and let c from the set C be a possible classification. Under the assumption of an independent feature, the conditional probability (prob) of x given c can be calculated as in equation (1):

$$prob(x|c) = \prod_{i=1}^{k} prob(x_i|c) \tag{1}$$

This equation also presupposes that the features $x_1, x_2, \dots, x_k$ are conditionally independent given the class c. Using this assumption, the classification c from C with the maximum posterior probability is determined as in equation (2):

$$prob(x|c) = {}^{max}_{c \in C} \left[prob(c) \times \prod_{i=1}^{k} prob(x_i|c) \right] \tag{2}$$

The learner approximates these probabilities by computing the respective frequencies in the training data set. Even though the class-conditional independence assumption may not be valid and there might not be enough probability information to be acquired, the NB classifier is still very useful and performs rather well in many scenarios.

Wide neural networks (WNN) are a type of neural network that contains multiple layers of interconnected nodes and can discover patterns and relationships in complex human data. Unlike traditional networks, WNNs consist of a large matrix that can handle multiple events. This suite is known for its flexibility and ability to process large amounts of data and is therefore used in various ML tasks such as classification, regression, and object-oriented learning [22].

The support Vector Machine (SVM): a supervised ML classifier that creates the best hyperplane from a set of feature vectors that are related to the types of a class-label dataset. The set of characteristic vectors $x_i \in R^n$, corresponding to the images I_i, $i \in [1, k]$ and the set of class labels is $y = (y_1, y_2, \dots, y_k)$. The problem here is to find the ideal linear hyperplane $w \cdot x + b = 0$, where w is the normal of the hyperplane and b is the translation constant. This better isolates the classes in Y, so that it increases the distance of the feature vector from the dividing hyperplane and reduces the number of negative elements assigned to the wrong labels. A cost parameter C and an error variable (ξ_i) (misclassification) are added if the data are non-linear and separable (equation (3)).

$$\xi_i = max(0,1 - y_i(w \cdot x_i + b)) \geq 0 \tag{3}$$

Introducing the misclassification penalty (error) into the searched hyperplane, which is an example of a more efficient SVM, eases the problem when the data are not accurately separated (equation (4))

$$\begin{gathered} (w \cdot x_i) + \ b \geq 1 - \xi_i \\ (w \cdot x_i) + \ b \leq -1 + \xi_i \\ \xi_i \geq 0\forall \end{gathered} \tag{4}$$

for y_i = 1 and y_i = –1 respectively. These disparities can be combined into a single equation using the class label (equation (5))

$$(w \cdot x_i + b) - 1 + \xi_i \geq 0 \ \forall_i \tag{5}$$

Figure 4 illustrates the function of an object to the maximum distance between hyperplanes and their parallels. The constraints are designed to minimize the penalty error while effectively separating the two classes using SVM with a linear kernel, which estimates the maximum margin between data. The distance between the hyperplanes is $\frac{2}{||w||}$, for the ideal distance a maximum $\frac{2}{||w||}$, which is equivalent to a minimum of $\frac{||w||^2}{2}$. In the end, we can write about the equation (6) that appears to be optimizing this problem:

$$\min\left(0.5\ ||w||^2 + c\sum_{i=1}^{k}\xi_i\right) \tag{6}$$

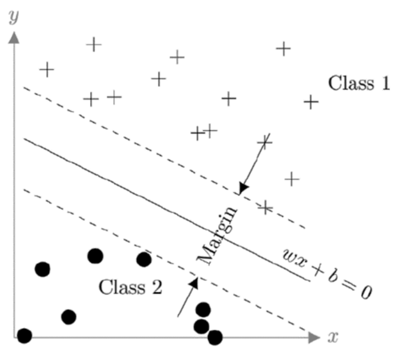

Fig. 4. A Leaner-SVM example of separation [23]

The Lagrange multiplier algorithm and the dual problem are convenient for solving the optimization problem mentioned above, since they allow the problem to be computed more efficiently [24].

4. Results and discussion

MATLAB 2022b was used to develop a hybrid architecture for transfer learning models, ResNet-18 and DenseNet-201, and classical ML classifiers such as SVM (linear and cubic kernels), WNN and NB. The hybrid structure used the final fc layer of the CNN models with these classification methods, and the ten iterations were tested. The model selection criterion used was based on the highest accuracy and the lowest standard deviation (SD), in line with the No Free Lunch (NFL) theorem that asserts that no single algorithm is optimal for all problems [25]. The training and testing data sets were divided into a ratio of 70:30. This evaluated the model as more rigorous and accurate since the model was tested on different data sets. To reduce the impact of data bias, samples were taken at random for each trial, which provided a broad perspective of the results. The performance of the model was evaluated using precision measures obtained from the confusion matrix for each classifier and hardness level [26].

Table 1 and Figure 5 show that the DenseNet-201 features classified by the SVM-Cubic kernel had the highest accuracy of $89.51 \pm 1.66\,\%$. This result shows the efficiency of the SVM-Cubic kernel when used with DenseNet-201 features, which is the best approach in this study.

Furthermore, Figure 6 shows an example of a confusion matrix that was used to calculate the accuracy for every level of hardness. The highest classification accuracy was recorded in apple slices with a high-hardness class of 94.3 % percent. This was followed by slices with low hardness, with an accuracy of 89 %, while slices with the medium hardness level had an accuracy of 83.45 %. This result shows the efficiency of the SVM-Cubic kernel when used with DenseNet-201 features. Thus, the proposed model is more effective in distinguishing between high hardness levels, which may be necessary for applications that need to classify a texture with high accuracy. The lower accuracy achieved in the classification of slices with medium hardness could be because the differences in the RGB values for these samples are not very significant and, therefore, the classification of such samples is more difficult. This suggests that there might be scope for further enhancement of the model, perhaps by adding more attributes or by trying other methods of classification.

Consequently, the proposed methodology was able to classify apple slices into different hardness levels with a high degree of accuracy, especially for higher hardness levels. These results highlight the applicability of integrating CNN architectures with other traditional ML classifiers for applications that require accurate and precise categorization, as in the case of apple slices post-harvest processing.

Table 1. The results of the proposed methodology are presented as the mean with the corresponding standard deviation (SD)

	SVM-Linear	Wide Neural Network	SVM-Cubic	Naïve Bayes
DenseNet-201	82.87(2.03)	86.6(2.69)	**89.51(1.66)**	72.53(3.61)
ResNet-18	80.11(1.64)	86.08(1.82)	88.02(2.1)	69.44(2.77)

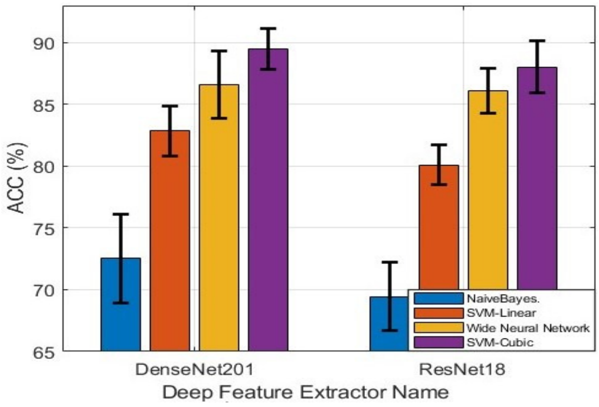

Fig. 5. The results of CNNs + ML classifier

The accuracy in the caret packets is defined as the overall accuracy using the predicted classes. The averages of the one-versus-all statistics are sensitivity and specificity. Equation (7) is used to calculate the overall accuracy is as follows [27]:

$$Accuracy = \frac{TP_{class1} + TP_{class2} + TP_{class3}}{Total\ number\ of\ test\ samples} \tag{7}$$

where TP_{class1} is positive true (low hardness); TP_{class2} is positive true (medium hardness); TP_{class3} is positive true (high hardness).

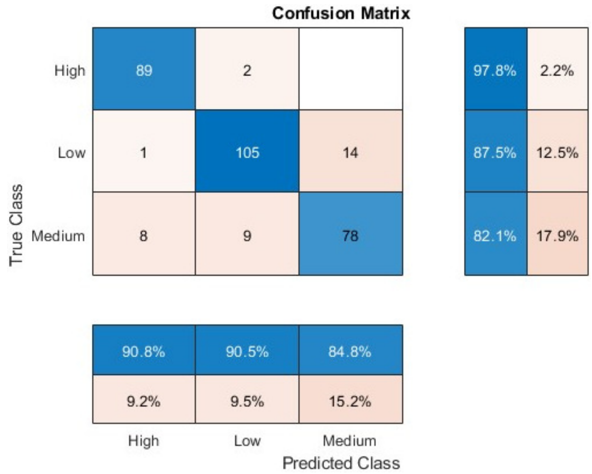

Fig. 6. An example of a confusion matrix of the results of DenseNet-201 combined with SVM-Cubic

To evaluate the performance of the classification models in this study, the Receiver Operating Characteristic (ROC) curve was used as depicted in Figure 7. This curve, which shows the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) when changing the discrimination threshold, was obtained for DenseNet-201 features classified by the SVM-Cubic kernel. This combination provided the highest accuracy and the lowest standard deviation of $89.51 \pm 1.66\,\%$. The Area Under the Curve (AUC), a measure of the performance of the classifier, was highest for the high hardness level at 0.98, for the low hardness achieved at 0.97, and finally 0.93 for the medium hardness level. The AUC gives the percentage of accuracy of the model in classifying between the two classes and is therefore a key measure for any classification model.

The ROC curve is a graphical representation of the TPR against the FPR at different threshold levels that can be calculated by the following equations (8) and equations (9) respectively [27].

$$TPR = \frac{TP}{TP + FN} \tag{8}$$

$$TPR = \frac{FP}{FP + TN} \tag{9}$$

The AUC stands for the area under the curve, and it is the probability that a randomly chosen positive instance will be ranked higher than a randomly chosen negative one, as defined in equation (10) [28].

$$AUC = \int_0^1 TPR(FPR)\, d(FPR) \tag{10}$$

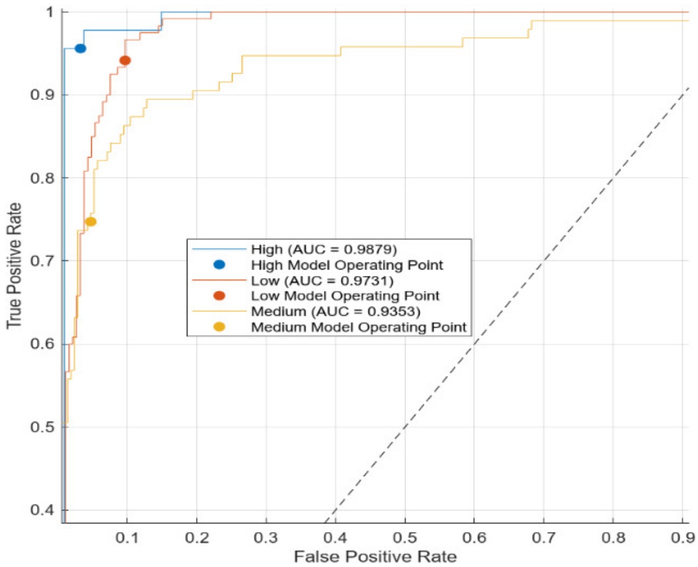

Fig. 7. Performance of a three-class classification system by adjusting the discrimination threshold

5. Conclusions

This study was able to show how CNNs can be used as feature extractors when used in conjunction with traditional machine learning classifiers to classify apple slices based on their RGB values. Using ResNet-18 and DenseNet-201 architectures together with classifiers such as WNN, NB, and SVM with Cubic and linear kernels, we were able to evaluate the effectiveness of hybrid models in identifying the hardness levels of apple slices. The DenseNet-201 features classified by the SVM-Cubic kernel provided the highest precision at 89.51 ± 1.66 %. This finding indicates that the aforementioned hybrid CNN+ML approach is effective, and it may be useful in future studies that involve the classification of objects with high accuracy, such as the postharvest quality assessment in the apple industry. However, the study also reemphasizes the fact that there is no one-size-fits-all solution in ML because the performance of a particular approach depends on the input features and the target output classes. Our method has an error rate of less than 11 % for custom datasets, and can be incorporated into applications such as smartphone applications for real-time apple slice hardness measurement. However, there are still some opportunities for improvement. Further research will be aimed at improving classification accuracy by investigating other features and classifiers, adjusting the parameters of the model, and increasing the number of samples for different levels of hardness. These are intended to improve the model's stability and generalizability of the model to other fields, making it more efficient in a broader context.

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