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Image-based orange (*Citrus Reticulata* and *Citrus Reticulata* Blanco) sweetness measurement by ResNet50

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Abstract

This research aims to develop a computer system that can evaluate an orange's sweetness from a single image. The system is called orange sweetness measurement system (OSMS). The system was used on 120 orange images taken from 20 video clips, each lasting 60 s. The system extracted 400 video frames as images from each video clip. It used 200 images to train the system and the remainder to validate it. The system employed ResNet50 to train, validate, and recognize orange images. It had eight procedures, 1) collecting oranges, 2) making orange video clips, 3) squeezing orange juice, 4) measuring orange sweetness with a refractometer, 5) training the dataset, 6) imaging to evaluate orange sweetness, 7) recognize an orange image, and 8) display recognition results and sweetness values. The precision rate of the system is 99.35%, with an average access time of 1.5248 s/image. Based on the experimental results, orange sweetness can be measured using only a single image.

Keywords: °Brix, convolutional neural network, image processing, orange, ResNet50, sweetness measurement

1. Introduction

Oranges are rich in nutrients and a very popular fruit cultivated around the world. The nutrients in oranges include total and saturated fats, cholesterol, sodium, total carbohydrates, dietary fiber, sugars, proteins, vitamins A and C, calcium, iron, thiamine, and folate [1]. Global orange production amounted to 76.29 million tons annually in 2020. Brazil is the largest orange producer (17.07 million tons). China produced 10.43 million tons followed by India with 9.50 million tons [2]. The sugar content of oranges is easily measured using a refractometer (ATAGO, Japan). Organic acids can be determined using a Phenomenex Luna RP-C18 (Phenomenex, Torrance, USA), and the microelement content can be determined using a Perkin Elmer Analyst 2000 atomic absorption spectrophotometer (Waltham, USA) [3]. There are primarily two techniques to measure an orange's sweetness, destructive and non-destructive measurements.

In sensory analysis, orange juice sweetness is evaluated using a human taste panel. Trained human sensory evaluation requires experts to evaluate orange sweetness [4-7]. For refractometer measurements, researchers cut each orange into pieces and squeezed orange juice from the pieces. A refractometer was employed to measure orange sweetness in °Brix units. One °Brix represents refraction (light bending) equivalent to that caused by 1 g of sucrose in 100 g of water [8]. Many researchers used refractometers to measure the sweetness of various orange species and found values of 7-22 °Brix and they verified their measurements with other non-destructive methods, namely soluble solids content (SSC), dry matter (DM), a monopole sensor, near-infrared (NIR) spectroscopy and computer simulation technology (CST) [9-14]. Both sensors and CST require complex equipment and highly trained operators. Other researchers developed computer software to evaluate orange sweetness by applying image processing techniques [15-17].

In the current study, image processing is employed as a non-destructive technique that correlates orange image attributes, color, texture, and shape using these attributes to predict fruit sweetness. Calvo et al. [18] added sugar to Spanish oranges to achieve 16.0 °Brix and measured their L*a*b* color values yielding, 80.09, 5.50, and 22.24, respectively. Fiona et al. [19] identified 350 Indian oranges in three categories, unripe, ripe, and infected with a precision of 90.0% using red, green, and blue (RGB) colors. Salaiwarakul and Mungklachaiya [20] classified 63 oranges into sweet and sour categories. Their experiments were conducted on four convolutional neural networks, ResNet50, Inception-V3, VGG16 and MobileNet-V2 with precision rates of 81.43%, 74.29%, 83.57%, and 79.29%, respectively. Adel Khani et al. [6] measured the sweetness of 300 Iranian oranges (Bam, Khooni and Thompson varieties) using orange image attributes that include RGB color, herpes simplex virus (HSV) component, texture, minor diameter, area, and circumference with a precision of 96.6%. Wang [21] predicted the sugar contents of 60 Japanese oranges by finding a relationship between their color and orange sweetness. Their experiments showed that orange sweetness decreased with greater green and yellow colors along with their hue.

Normally, classifying orange quality using visual appearance is labor-intensive and costly. Machine vision is an alternative method to solve these problems. Therefore, the objective of the current research is to validate the hypothesis that an orange's sweetness can be predicted from a single image. The details of system design, implementation, and evaluation are presented with a discussion of results in the following sections.

2. Materials and methods

2.1 Orange samples

This research employed 55 Sai Num Phung oranges (*Citrus reticulata* Blanco) and 65 Mandarin oranges (*C. reticulata*) purchased at Thon Buri Market, Phutthamonthon Sai 2, Bangkok, Thailand. The Sai Num Phung oranges are a local product while the Mandarin oranges were imported from Chinese Taipei. The Mandarin variety has a more orange color than Sai Num Phung and they tend to be sweeter. Images of Sai Num Phung and Mandarin oranges are shown in Figures 1(A)-1(B), respectively. All oranges used in this research were evaluated within one week of purchase. The experiments were done in July–August 2023 when ambient temperatures were around 28–32 °C. Each orange was placed on acrylic plastic, which helped to position it when making video clips. The experiments were conducted under ambient lighting conditions. Lighting was not controlled when making the video clips. The system hardware and software are described in the next section.

Figure 1 Samples of orange images used in this research: (A) Sai Num Phung, (B) Mandarin oranges.

2.2 System hardware and software

The OSMS was developed with standard computer hardware and software. The central processing unit employed an AMD Ryzen 7 PRO 5850U operating at 1.90 GHz with 16 GB of RAM. A Windows 11 operating system was used. The software was developed with MATLAB R2020b (License Number 40598465). The system employed the ResNet50, which is the MATLAB toolbox for image recognition, and Microsoft Excel to record OSMS data. A Xiaomi Redmi Note 8 mobile camera was used to make orange video clips. The Redmi Note 8 camera specifications are: 1) picture resolution = 48 MP, 2) aperture = f/1.8, 3) periscope telephoto = 26 mm (wide), 4) sensor size = 1/2.0", 5) pixel size = 0.8 µm, and 6) number of video frames = 4K@30fps. A portable refractometer model FG-113 (ATAGO, Japan) was used to measure light refraction in °Brix.

2.3 Convolutional neural networks

Convolutional neural networks (CNNs) are powerful image-processing methods to identify unknown images with high accuracy [22]. This research project employed ResNet50, which is a type of CNN, to recognize orange images. ResNet50 has three primary functions, feature extraction, classification, and output classification, (Figure 2). Operation of ResNet50 involves the following steps. First, an input image is acquired. Then, feature extraction is repeated in the convolution and pooling layer until it extracts all the input image features. Second, the full connection component uses all features of a neural network input layer and classifies an input image that is presented to an output layer. Finally, the output classification component displays the most similarity between the input image and images in the dataset.

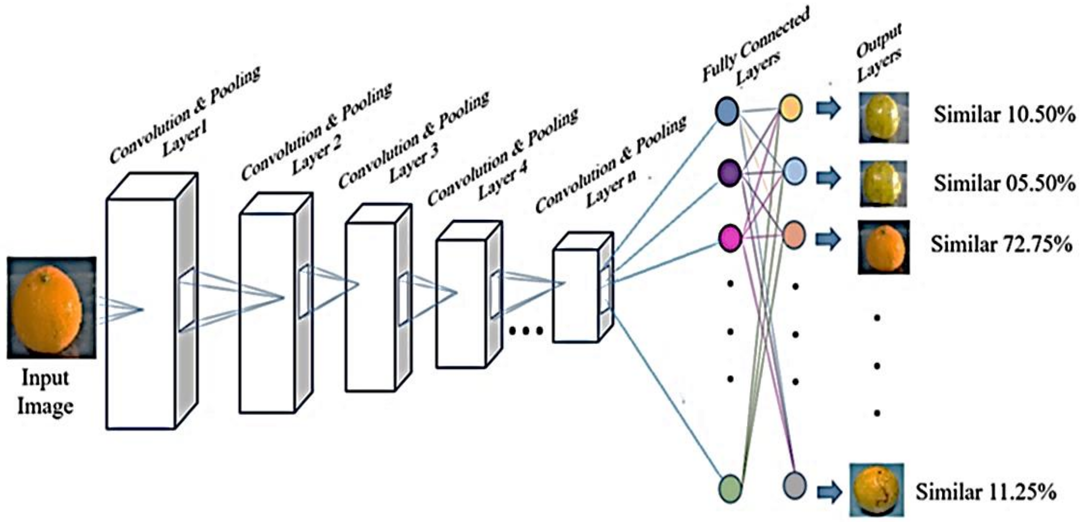


Figure 2 Structure of a convolutional neural network.

2.4 System conceptual diagram

The OSMS conceptual diagram starts with the user taking a photograph of an orange. Then, the image is submitted to the system to evaluate its sweetness. After that, the OSMS retrieves the most similar orange image among all the orange images in the dataset. Finally, the system displays a range of predicted sweetness values, from the lowest to the highest, for an orange image input (Figure 3).

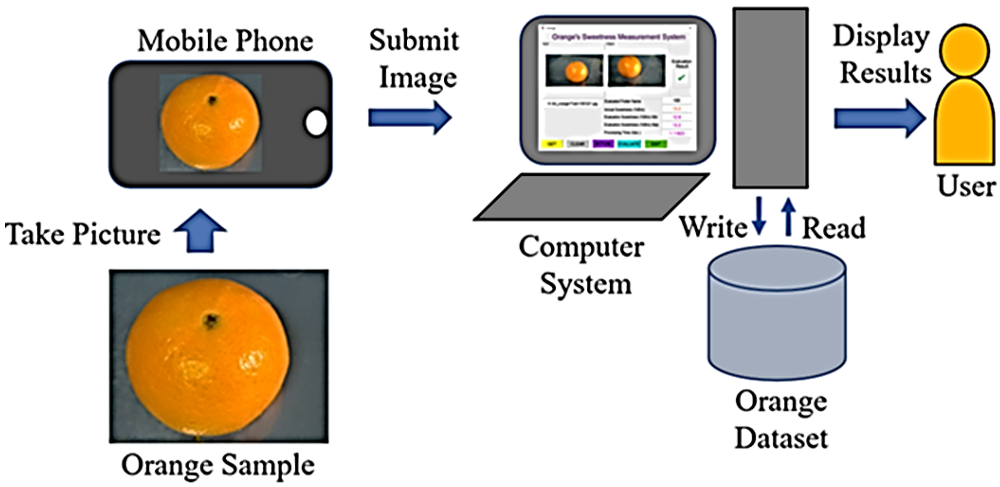


Figure 3 OSMS conceptual diagram.

2.5 System flowchart

The OSMS flowchart consists of eight main processes, 1) collecting oranges, 2) make a video, 3) squeeze orange juice, 4) measure sweetness using a refractometer, 5) train the ResNet50 dataset, 6) make orange photograph, 7) image processing by ResNet50, and 7) display evaluation results (Figure 4).

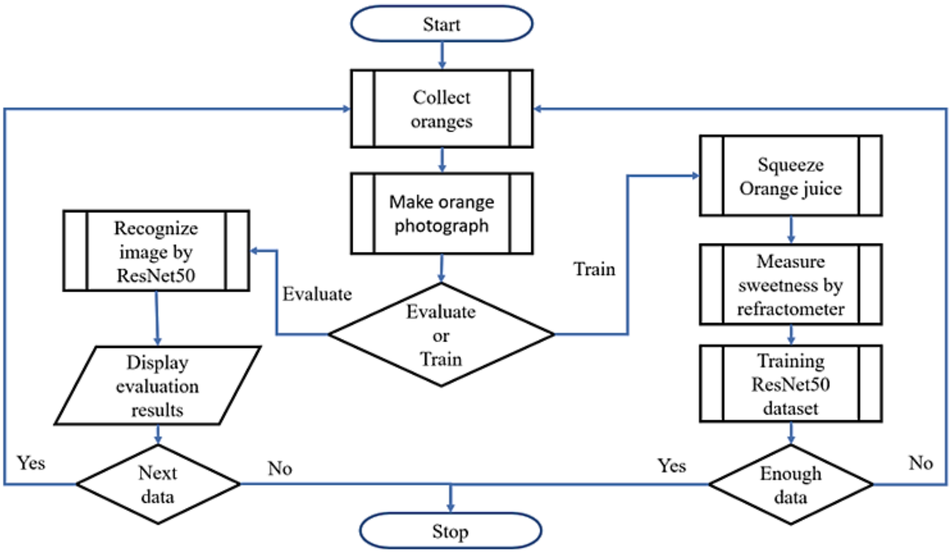


Figure 4 OSMS flowchart.

2.5.1 Collect orange

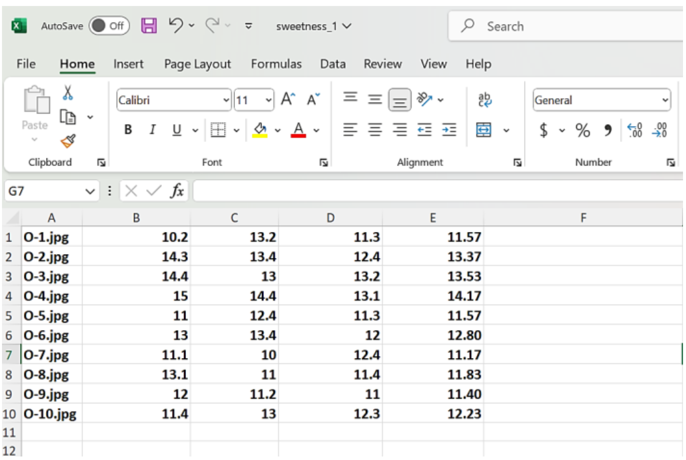
Oranges were prepared for videography and photography. Then, their sweetness was measured with a refractometer. All the oranges were cleaned and labeled with a running number on their skin to avoid mismatches between the orange images and their sweetness measurements. There are two processes after the collect orange procedure, training more data into the system dataset and evaluating the system. The training system dataset requires four steps, making video clips, squeezing orange juice, measuring sweetness with a refractometer, and training the ResNet50. System evaluation consists of three processes, making photographic images, orange image recognition, and displaying evaluation results. Each process is described below.

2.5.2 Making video clips of oranges

This experimental step was done by placing a mobile phone camera on a selfie stick and positioning an orange on acrylic plastic. After that, each orange was spun on its axis during a 60 s video clip. Finally, MATLAB was used to extract information from the orange video clip by sampling one of every 10 video frames.

2.5.3 Squeeze orange juice

This process randomly selected 3 orange pieces, squeezed each piece into orange juice, and placed a drop of orange juice on a refractometer prism to measure its sweetness. Sweetness of each orange fruit was measured three times, and the resulting values were recorded in a Microsoft Excel spreadsheet. A sample spreadsheet is shown in Figure 5. Column A is the orange image's file name, while columns B, C, and D are three measured orange sweetness values in °Brix. Finally, column E is the average orange sweetness value.



	A	B	C	D	E	F
1	O-1.jpg	10.2	13.2	11.3	11.57	
2	O-2.jpg	14.3	13.4	12.4	13.37	
3	O-3.jpg	14.4	13	13.2	13.53	
4	O-4.jpg	15	14.4	13.1	14.17	
5	O-5.jpg	11	12.4	11.3	11.57	
6	O-6.jpg	13	13.4	12	12.80	
7	O-7.jpg	11.1	10	12.4	11.17	
8	O-8.jpg	13.1	11	11.4	11.83	
9	O-9.jpg	12	11.2	11	11.40	
10	O-10.jpg	11.4	13	12.3	12.23	
11						
12						

Figure 5 Sample spreadsheet of orange sweetness values.

2.5.4 Measuring sweetness with a refractometer

A refractometer is a simple instrument used in the current study to measure a fruit's sweetness. It works by passing light through a liquid and projects its refraction angle on a scale. Liquids refract to varying angles depending on the types and concentrations of substances dissolved in the liquid.

2.5.5 Training the ResNet50 dataset

The OSMS employed the ResNet50, which is a component of the MATLAB toolbox. The system employed ResNet50 in training, evaluating, and recognizing the orange images. The OSMS used 120 orange video clips in an MP4 file format and extracted 200 images from each video clip into a JPG file format for system training. Another 200 images were retrieved to evaluate the system. The training images were extracted from only odd-numbered frames and skipped ahead every 10 frames (1, 11, 21, 31, etc.), while the evaluation images were extracted from even-numbered frames, also skipping ahead every 10 frames (2, 12, 22, 32, etc.). There were 24,000 (120 X 200) images to train the system, from which 19,200 (24,000 X 0.8) were randomly selected. The remaining 4,800 (24,000 X 0.2) images were used to test the ResNet50.

2.5.6 Making images of oranges

This research employed a mobile phone to make orange images in a JPG file format. Then, orange images were submitted to the OSMS. This research used 1080 X 1920 X 3 (width X height X plane) pixel images. The distance between the mobile phone camera and orange was around 30 cm.

2.5.7 Image recognition by ResNet50

The OSMS also employed ResNet50 in MATLAB to recognize orange images and to evaluate their sweetness. This research validated ResNet50 using 24,000 (120 X 200) images. Each image had 1080 X 1920 X 3 (width X height X plane) pixels. ResNet50 transformed every input image into 224 X 224 X 3 pixels before image recognition.

2.5.8 Display evaluation results

This process showed the recognition results. A graphic user interface (GUI) of the OSMS is shown in Figure 6. The GUI has three main components, 1) three graphic windows, 2) six text boxes, and 3) five buttons.

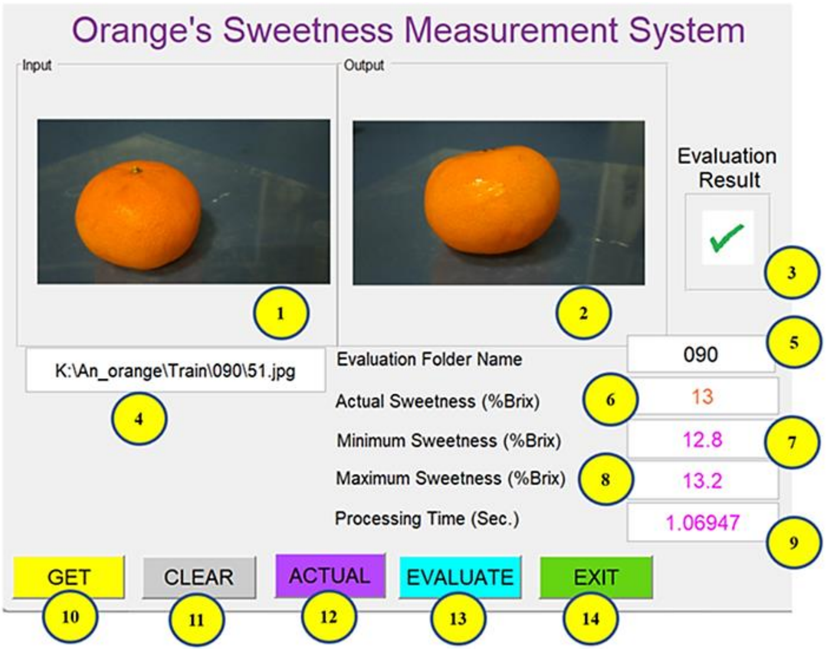


Figure 6 GUI of the OSMS.

The three graphic windows are to 1) input the orange image, 2) output a recognized orange image, and 3) show sweetness evaluation results, as respectively shown by labels 1, 2, and 3 in Figure 6.

The six text boxes show the 1) input file name, 2) evaluation folder name, 3) actual orange sweetness, 4) minimum predicted orange sweetness, 5) maximum predicted orange sweetness, and 6) evaluation processing time, as respectively indicated by labels 4-9 in Figure 6.

The five buttons are the 1) get image, 2) clear image, 3) show actual orange sweetness, 4) show orange sweetness evaluation, and 5) exit program buttons, as respectively indicated by labels 10-14 in Figure 6.

2.6 Statistical analysis

OSMS employed four statistical parameters to evaluate the system performance, 1) accuracy, 2) precision, 3) recall, and 4) F1-score. Each statistical value has the following details.

2.6.1 Accuracy

Accuracy represents the number of correctly evaluated data instances divided by the total number of data instances, as shown in Equation 1.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

2.6.2 Precision

Recall illustrates the number of correct evaluations divided by the total number of true positives and false negatives, as shown in Equation 2.

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

2.6.3 Recall

F1-score is the harmonic means of precision and recall. It is calculated as two times the product of precision and recall divided by the sum of precision and recall, as shown in Equation 3.

$$F1 - Score = \frac{2\ X\ Precision\ X\ Recall}{Precision+Recall} \tag{3}$$

3. Results and Discussion

3.1 Experimental Results

The OSMS used 120 oranges in these experiments. They consisted of 55 local (Sai Num Phung) and 65 imported (Mandarin) oranges. It used 120 video clips of 120 oranges in full HD format for 60 s each. After that, the system extracted 48,000 video frames from 120 video clips. Of these, 24,000 orange frames were used to train the system, and the other 24,000 images were employed to validate it. Based on the experimental results, the relationship between the fruits' RGB colors and their sweetness is shown in Table 1. Mandarin oranges were sweeter than the Sai Num Phung variety. Their images had RGB color values between 206–251, 88–169, and 0–28, respectively, with sweetness values of 10–16 °Brix. The Sai Num Phung variety had RGB color values between 188–221, 134–167, and 1–8, respectively, while their sweetness was 7–12 °Brix.

Table 1 Relationship between fruit color and sweetness values.

Orange variety	Red	Green	Blue	Sweetness (°Brix)
Mandarin	200-251	88-169	0-28	10-16
Sai Num Phung	188-221	134-167	1-8	7-12

Table 2 OSMS training of the dataset confusion matrix.

	Actual class	
	Positive	Negative
Prediction Positive	23,844 (TP)	156 (FP)
Prediction Negative	156 (FN)	1,703,844 (TN)

TP = true positive, FP = false positive, FN = false negative, TN= true negative

Table 3 OSMS validation of the dataset confusion matrix.

	Actual class	
	Positive	Negative
Prediction Positive	22,632 (TP)	1,368 (FP)
Prediction Negative	1,368 (FN)	1,702,632 (TN)

TP = true positive, FP = false positive, FN = false negative, TN= true negative

The OSMS employed 24,000 orange images to train the ResNet50 to create the OSMS dataset with a 99.35% precision. Moreover, the OSMS also used a distinct set of 24,000 orange images to validate the ResNet50 with a precision of 94.30%. The confusion matrix of the OSMS training dataset is shown in Table 2, which had 23844 (24,000 X 0.9935) true positive (TP) values, 156 (24,000 X 0.0065) false positives (FP), 156 (24,000 X 0.0065) false negatives (FN), and (1,703,844 (120 * 120 *120) – (23,844 + 156 + 156)) true negative (TN). The OSMS validation of the confusion matrix is shown in Table 3, which had 22,632 (24,000 X 0.9430) true positives (TP), 1,368 (24,000 X 0.057) false positives (FP), 1,368 (24,000 X 0.057) false negatives (FN), and (1,702,633 (120 * 120 *120) – (22,632 + 1,368 + 1,368)) true negative (TN).

The accuracy and loss graphs for training the ResNet50 are shown in Figures 7(A) and 7(B), respectively. Parameters for training the ResNet50 include an epoch per iteration, a 0.01 learning rate, and a maximum of 16 epochs. Correct and incorrect sweetness evaluation results are illustrated in Figures 8(A) and 8(B), respectively, based on the experimental results. In Figure 8(A), the actual sweetness is 13.2 °Brix but the evaluated sweetness is between 12.8–13.2 °Brix with an access time of 1.11823 s. In Figure 8(B), the actual sweetness is 15.2 °Brix but the evaluated sweetness is between 9.8–10.2 °Brix with an access time of 1.22969 s.

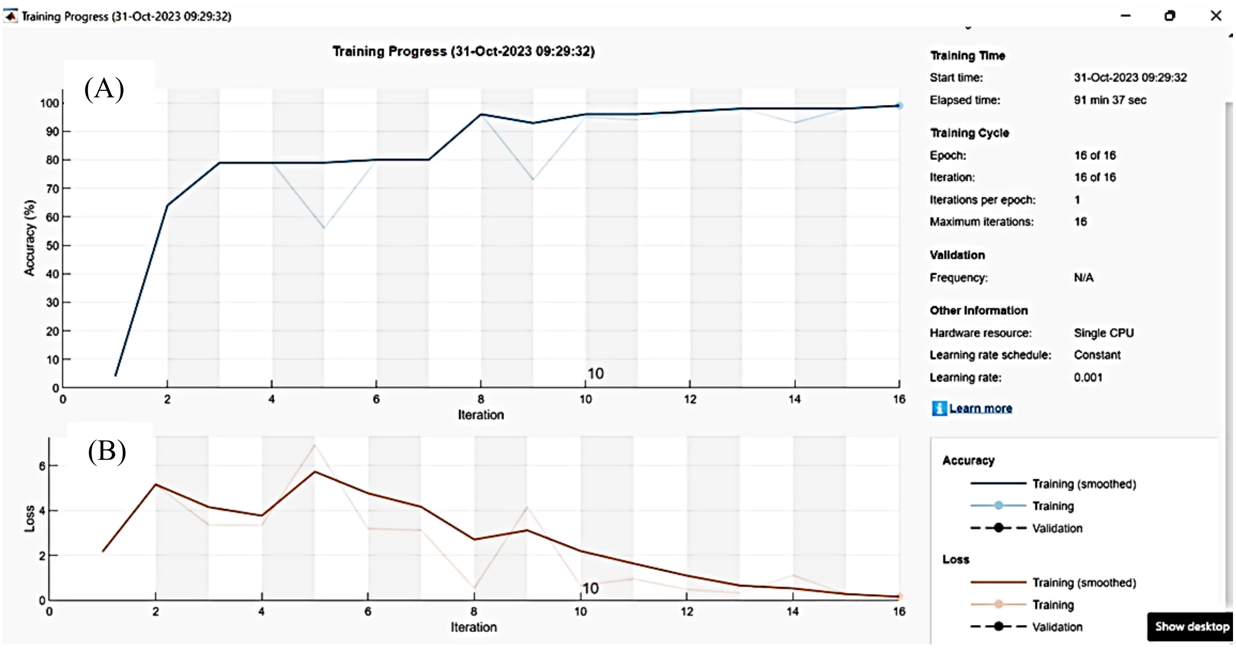


Figure 7 (A) Accuracy and (B) loss curve for training the ResNet50 in the OSMS.

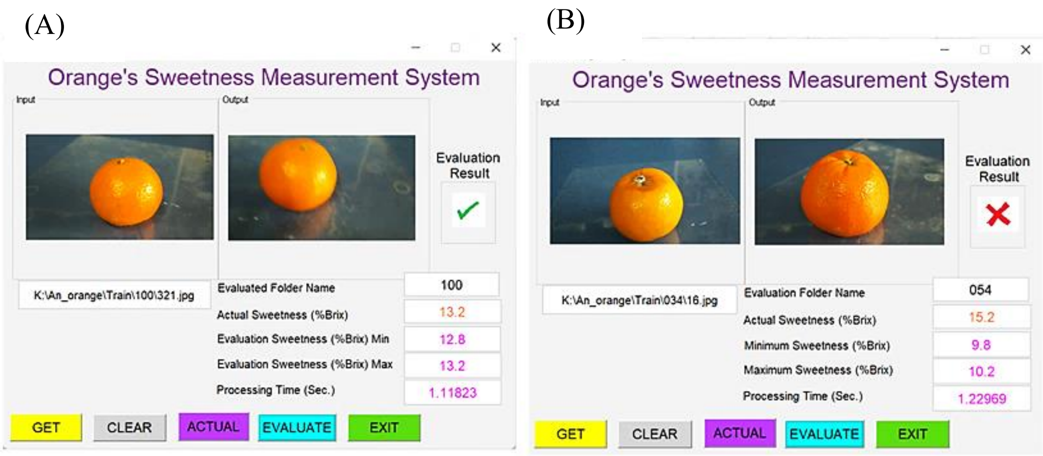


Figure 8 The OSMS GUI screen (A) correct evaluation (B) incorrect evaluation.

The OSMS was used to conduct further experiments comparing its performance among various CNNs, including 1) Alex Net, 2) Google Net, 3) Inception-V3, 4) ResNet18, 5) ResNet50, 6) ResNet101, and 7) VGG16, using the same dataset. The statistical parameters employed to compare CNN performance were 1) accuracy, 2) precision, 3) recall, 4) F1-score, and 5) training dataset time, as shown in Table 4. All these CNNs are supported by the MATLAB toolbox. Based on the experimental results, the Alex Net had the lowest accuracy, precision, recall, and F1-scores, while VGG16 had the shortest training dataset time. However, the ResNet50 had the highest accuracy, precision, recall, and F1-scores, while the Inception-V3 had the longest training dataset time. Therefore, ResNet50 was selected to train using the orange dataset and recognize orange images due to its highest performance among the evaluated CNNs.

Table 4 Performance comparison among various CNNs.

CNN	Accuracy	Precision	Recall	F1-Score	Training Time (s)
AlexNet	18.40	20.87	18.40	19.56	382.7
GoogleNet	98.48	98.54	98.48	98.51	1,045.4
Inception-V3	92.06	93.51	92.06	92.78	2,312.1
ResNet18	94.58	95.16	94.58	94.87	1,420.4
ResNet50	99.35	99.33	99.35	99.34	921.6
ResNet101	18.23	31.37	18.23	23.06	2,294.8
VGG16	21.17	29.26	21.17	24.57	354.9

3.2 Discussion

Numerous researchers have used image-processing techniques to evaluate fruit sweetness. Sangsongfa et al. [23] employed a CNN to predict pineapple sweetness from their images. Their system used 4,860 pineapple images with an 80.15% accuracy. Pornpanomchai et al. [24] evaluated banana sweetness using digital image processing achieving an 80.18% precision [24]. Salaiwarakul and Mungklachaiya [20] classified sour and sweet oranges using various CNN models, MobileNet-V2, Inception-V3, VGG-16 and ResNet50 with an 83.57% accuracy [20].

Based on previous research, image-based techniques are among the best non-destructive methods to measure fruit sweetness. The current study hypothesizes that an orange's sweetness can be determined from a single image. The common orange image features employed in previous research included color, texture, and shape attributes [6]. A comparison of orange sweetness predictions by various image processing methods is shown in Table 5. Salaiwarakul and Mungklachaiya [20] classified only sweet and sour oranges by CNN and confirmed the experimental results with human sensory evaluation. The current study evaluated orange sweetness comparing results of an image processing method with refractometer measurements of actual orange sweetness. The oranges in Table 5 were compared using various image processing methods to determine orange sweetness. They were from various countries with different sample sizes. Therefore, it is difficult to compare these experimental results.

Nevertheless, state-of-the-art precision rates to evaluate orange sweetness were higher than 90.00% with sweetness values of around 8–16 °Brix.

Table 5 Comparison of various image processing methods of measuring orange sweetness.

Authors	Country	Method	°Brix	Precision	Sample size
Adelkhani et al. [6]	Iran	ANN+Fuzzy	N/A	96.60%	300 fruits
Salaiwarakul and Mungklachaiya [20]	Thailand	CNN	N/A	83.57%	200 images
Sammarraie [2]	Egypt	KNN + NN	12-15	97.00%	50 fruits
Wang [21]	Japan	RGB color	9-16	N/A	60 fruits
This Research	Thailand	CNN	8-16	99.35%	48,000 images

4. Conclusions

The OSMS fulfills the objective of this research, which is to develop a computer system for evaluating orange sweetness from a single image. The OSMS dataset consists of 24,000 images from 120 oranges. The average system accuracy is 99.35% for training the dataset and 94.30% for system validation. The average access time of the system is 1.5248 s/image. This research can help traders, farmers, and consumers to evaluate orange quality. Moreover, researchers can apply techniques used in this research to measure the sweetness of other kinds of fruits.

5. Acknowledgments

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