iBanana: Intelligent Method for Banana Ripeness Detection and Analysis using Convolutional Neural Network

Andi Bese Firdausiah Mansur*, Arwa Abdulwahab Mashat, Nouf Al-mohammadi

Faculty of Computing and Information Technology in Rabigh, King Abdulaziz University, Jeddah, Saudi Arabia

Summary

Researchers have demonstrated that teaching children could be improved by using technology to teach them rather than by following traditional methods to instruct them about detecting fruit ripeness, which is one of the challenging problems in harvesting fruit for farmers. Most farmers still rely on manual inspection to check the ripeness of fruits. An innovative solution using computer vision and artificial intelligence might help people select fruit based on its color intensity in order to harvest the best quality fruit. This project detects banana fruit quantity and ripeness using computer vision based on seeing, recognizing and analyzing an image. To capture fruit from a photo, the system must go through phases to process each layer of the given image. The system recognizes the quantity and ripeness of fruit using image-based computer vision and deep learning. This system uses a convolutional neural network (CNN) to analyze fruit images after a person (user) first uploads an image. The system compares the classifier image with a stored image in the dataset from the disk. Using the pretrained model VGG16, the system achieves more than 95% accuracy in detecting fruit ripeness. This system is expected to be helpful in the hands of the people who collect fruit based on their knowledge and reliability, to make sure they buy a good grade of fruit.

Keywords:

Fruit ripeness, Artificial Intelligence, Convolutional neural network

1. Introduction

Fruit ripeness is one of the success factors affecting the harvesting fruit industries. The quality of harvested fruit will affect profit, shipping time and even the prediction of market prices. Usually, a farmer performs a manual inspection to detect when fruit is ripe, and such detection techniques are based on a farmer's previous experience. Therefore, automation of fruit ripeness detection will help society, and it will be achieved by combining computer vision techniques and artificial intelligence to automatically detect fruit ripeness. Wu et al. proposed an innovative approach to recognizing tomato ripeness based on a relevance vector machine (RVM) and a bilayer classifier. Their process involves two stages of classifications: using color difference information to detect regions of tomatoes, and at the same time, the type of each tomato is based on multimedium features [1]. Fernández et al. [2] developed adaptable multisensory and associated preprocessing algorithms to locate and detect fruit in natural conditions among different crop varieties. Furthermore, Gan et al. proposed an approach to see green and immature fruits, combining colorful and thermal images [3]. Previous researchers have focused on detecting and identifying immature green citrus fruits and counting them using external color images. This system intended to develop an early productivity mapping system with multiple features that have been combined to remove some false-positive results [4]. Csillik et al. projected a detection and identification system for crops and citrus fruits using a convolutional neural network (CNN). Unmanned Aerial Vehicle (UAV's) obtained the images. Then, using a simple linear iterative clustering (SLIC) algorithm, the superpixels were derived and used to improve classification [5]. Based on previous related works, we can conclude that ripeness detection is essential for farmers and the fruit industry to avoid harvesting immature or poor quality fruits. This paper consists of several sections. Section 1 presents the background of the study, while segment 2 discusses related works. Section 3 describes the methodology of the research, while Chapter 4 describes the results of the study. Finally, Part 5 provides conclusions about the research and offers suggestions for future work to be undertaken in upcoming research.

2. Related Works

Fruit ripeness is often determined by characteristics, such as size, weight, color characteristics, fruit aroma, etc. It is possible to identify the characteristics of the ripeness of the fruit by the color of the fruit peels; the examination of such color characteristics of fruit peels is an important factor in determining fruit ripeness and also a relatively easy way to determine ripeness, as well [1][2]. Therefore, the robotic system we propose will greatly assist the community, including farmers, by combining computer vision technology with artificial intelligence, and by using tags on objects in images with the emergence of graphic annotation tools; this effective discovery is achieved using the framework Faster R-CNN [3]. Senthilnath et al. proposed a method using a UAV that uses the Bayesian information criterion (BIC) to determine the optimal

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number of clusters in RGB images captured by the UAV. These clusters are used to detect tomatoes using spatial spectral methods in images, and more than one method is used to classify pixel units into two groups [6]. Stein et al. developed a solution to the problem of mango fruits, which is the problem of occlusion, and used the multiple viewpoints method to analyze a sequence of images to track the fruits and determine their location. Unfortunately, the performance of this method in real time is weak and not very effective [7]. Kestur et al. created Mango Net, an architecture based primarily on a CNN; they performed many experiments and made it clear that their system performed better than FCNs (fully convolutional networks) [8]. Bargoti et al. maintain that ground-based imaging equipment has been used in most studies to detect fruit on trees. This equipment needs to move slowly, is affected by the type of terrain, and requires that the imaging equipment move from place to place. Such an approach is time consuming, so a UAV was used instead in their study for easy and comprehensive imaging [9]. Velez - et al. proposed using the ripening index (RPI), which is a standard factor in assessing the maturity stages of some fruits. They used this indicator to link several criteria, including sugar content, fruit firmness and acid ratio, to determine maturity and recommended this indicator as having value [10]. Vasquez-Caicedo et al. used RPI indexing in performing mango classification and detecting maturation stages by color [11]. Barnea et al. developed a three-dimensional method based on several factors: including shape and color neutral attributes to detect fruits with harvest robots. They proposed the use of two technologies, first using RGB images and second using range data, to analyze the shape features of target objects at the image level as well as in three-dimensional space. Extracting features and then making choices based on such features is a challenge in improving the accuracy of identifying objects on any computer. In the detection and classification of images, deep learning curricula have been widely used in recent years [12]. Stajnko et. al propose a system where a deep neural network (DCNN) approach is used to combine multimedia feature techniques to improve single-feature DCNN networks. Three types of multimedia features are used: first RGB features, second near-infrared features, and third NIR features [13]. Ren et al. developed a new multisensor framework to identify and track each piece of fruit and to determine its location by combining the technology of a faster region-based neural network (faster R-CNN) with the LiDAR data being mapped [14].

Kleynen et al. states that in classification-based methods, pixels are divided into different categories and are processed using many classification methods [15]. Leemans et al. proposed that pixel units in the image be compared to a preprepared computed model and then classified as mature or defective. Classification measures achieved in this study were not good due to a lack of target values and because the technique was not subject to guidance [16]. Krizhevsky et al. commonly used a method for detecting fruit from images using region detection with CNN features. R-CNN wraps all the suggested fruit pixels in a bounding box tightly, and sometimes the suggestion information can be changed [17]. Next, the Fast R-CNN model adds a spatial pyramid pooling module developed to detect objects [18]. Korostynska et al. assessed strawberry maturity in a very short time, in real-time, based on an electromagnetic wave sensor using microwave spectroscopy [19].]. Table 1 presents a detailed comparison of previously proposed techniques for the detection of fruit ripeness.

Table 1. Contribution technique with previous works

	Authors	Related works	Methods
1	Bassil and Wu et al.	Fruit ripeness is often determined by some characteristics, such as size, weight, color characteristics. It is possible to identify the characteristics of the ripeness of the fruit by the color of the fruit peels	**The system determines the ripeness of the fruit by color.**
2	Kestur et al.	The creation of Mango Net, an architecture based primarily on CNN; made it clear that it performed better than FCNs (fully convolutional networks)	**Focused on Mango tracking using CNN**
3	Bargoti et al.	Ground-based imaging equipment has been used in most studies to detect fruit on trees, and that takes time, so a UAV has been used for easy and comprehensive imaging	**Focus on detecting the fruits on the tree**
4	Vasquez-Caicedo et al.	Use (RPI) indexing in mango classification and maturation stages by color	**Use Faster R-CNN to make a bounding box around the fruit of interest**
5	Leemans et al.	The pixel units in the image are compared to a preprepared computed model and then classified as mature or defective.	**Fruit is identified by calculating (IoU). Then, by (CNN) the vital region**

			is determined by Region Proposal Network (RPN) to recognize the fruit's ripeness.
6	Krizhevsky et al.	Commonly used method for detecting Fruit from images is region detection use with CNN features. R-CNN wraps all the suggested fruit pixels in a tight bounding box. Sometimes the suggestion information can be changed.	**The input initially propagated (or sent) through VGG16 giving, a deep CNN.**
7	Korostynska et al.	To assess strawberry maturity in a very short time, in real-time, based on an electromagnetic wave sensor using microwave spectroscopy	**Using electromagnetic wave sensor.**

3. Research Method and Material

The proposed system recognizes the ripeness of fruit through color. The following methodology collects a different fruit image for the dataset for the learning process. Then, it continues with data augmentation, such as cropping, padding, horizontal flipping, zooming, rescaling, and more using Keras. As a next step, it trains the classifier using TensorFlow or OpenCV and then saves the disk's fruit classifier. Next, the fruit's ripeness detector is applied by loading the fruit's ripeness classifier from the disk. The system uses a transfer learning technique to build the model. Transfer learning takes a model trained on a larger dataset and applies its knowledge to learn a second much smaller dataset. In our case, we will use the pretrained model VGG16 and convert it to classify between three categories. The fruit classifier is applied to all fruit to analyze and detect the fruit's ripeness by color (overripe, ripe, unripe). After completing the analysis, the results are presented where each result consists of the name of the fruit and its ripeness. The detailed diagram is shown in Fig.1.

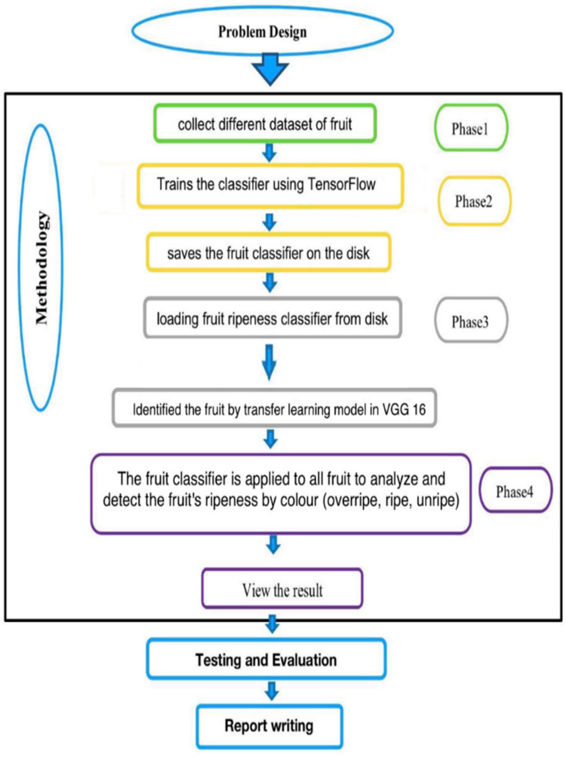


Fig. 1. Project Methodology

To analyze an image, the user first needs to upload a picture of the fruit. Once the system receives the specific requirement, it will start studying through a series of operations. After capturing the image, we will train the system with TensorFlow/Keras and then start using the classification module. The input is initially propagated (or sent) through VGG16, giving a deep CNN that includes two layers: convolutional and fully connected layers. The final convolutional layer's output will display a high-dimensional feature map to enable the system to generate data with a fit generator. The system predicts the classified object in the image based on the categories in the dataset. The details of the process are depicted in Fig.2.

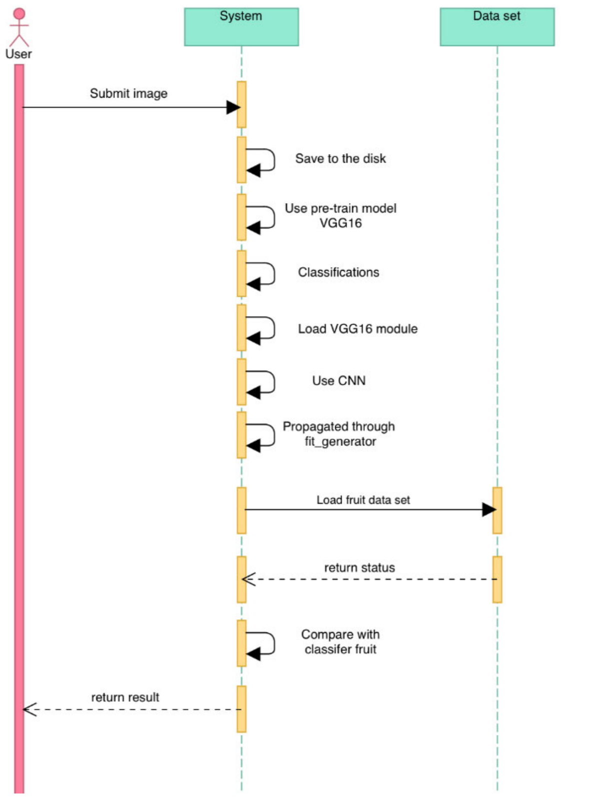


Fig. 2. Sequence diagram for image analysis

The process uses a classification module to classify individual regions in the image to make a bounding box around the fruit. An image's input is initially propagated (or sent) through a deep CNN (VGG16) containing conventional and fully connected layers. Based on TensorFlow, Keras and OpenCV, we have developed a system to detect fruit ripeness via the Jupyter notebook framework. Therefore, training the dataset with a CNN improved how the system recognized ripeness in the fruit. As planned, we settled on preparing one fruit, Banana fruit, as shown in Fig.3.

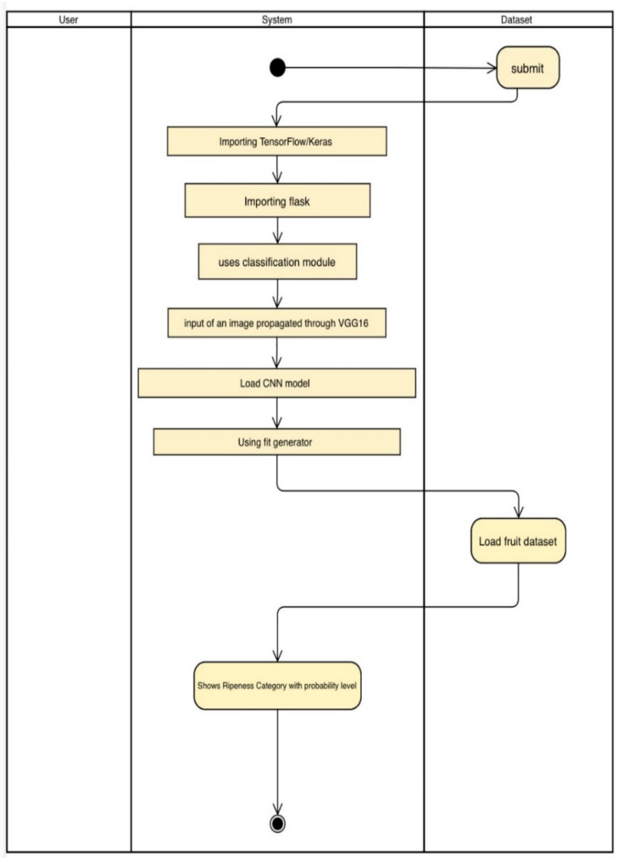


Fig. 3. Activity diagram for image analysis

The architectural design phase in Fig. 4 is a critical phase that includes the description and design of the system's structure and dataset and the demonstration of its relationships.

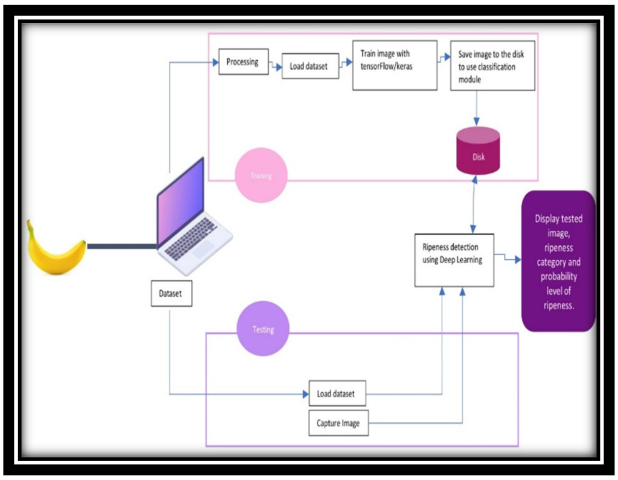


Fig. 4. System Architecture and Design

4 Result and Discussion

After To determine fruit ripeness through uploading images, customers can use their app.py files shown in Fig.5. A training process is required to improve the accuracy of the tracking results, and Banana.py is used to train the detector. Users have two options: either upload an image or capture an image in real time; real-time images are captured via a webcam. As shown in Fig.6, the training epochs are followed by four parameters: loss, accuracy, value_loss and value_accuracy. Refer to Fig.6 values of the four parameters to see the results of repeating this process during training. The training process starts with each new training epoch. We used a CNN with pretrained model VGG16 to improve the accuracy of classifications.

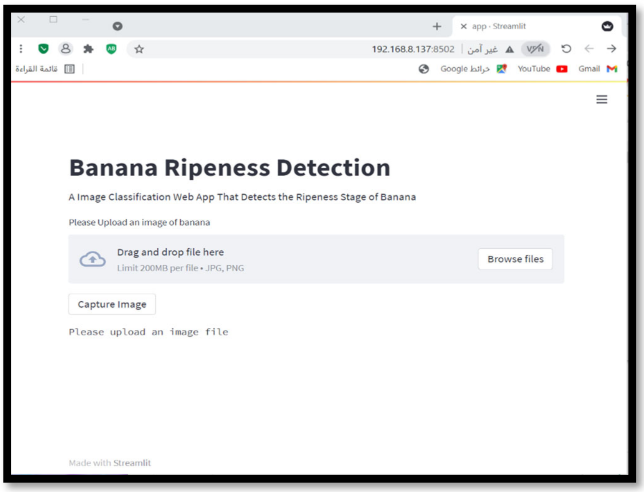


Fig. 5. Main interface of the proposed system

When the training process is complete, the results will be displayed as depicted. For the given dataset, the classification accuracy was more than 95%. Before the coding started, we collected a dataset of banana fruits, which were classified into three categories (Ripe, Unripe, and Overripe). Then, our analysis continued by applying data augmentation techniques using Keras: cropping, padding, horizontal flipping, zooming and rescaling, as shown in Fig.7.

```
Epoch 13/25
576/576 [==============================] - 82s 142ms/step - loss: 0.0623 - accuracy: 0.9811 - val_loss: 0.2637 - val
_accuracy: 0.9364
Epoch 14/25
576/576 [==============================] - 81s 141ms/step - loss: 0.0580 - accuracy: 0.9847 - val_loss: 0.0033 - val
_accuracy: 0.9976
Epoch 15/25
576/576 [==============================] - 81s 141ms/step - loss: 0.0331 - accuracy: 0.9906 - val_loss: 0.0779 - val
_accuracy: 0.9731
Epoch 16/25
576/576 [==============================] - 81s 141ms/step - loss: 0.0443 - accuracy: 0.9890 - val_loss: 0.0111 - val
_accuracy: 0.9951
Epoch 17/25
576/576 [==============================] - 82s 142ms/step - loss: 0.0274 - accuracy: 0.9922 - val_loss: 0.0092 - val
_accuracy: 0.9951
Epoch 18/25
576/576 [==============================] - 82s 142ms/step - loss: 0.0358 - accuracy: 0.9890 - val_loss: 0.0096 - val
_accuracy: 0.9976
Epoch 19/25
576/576 [==============================] - 81s 141ms/step - loss: 0.0544 - accuracy: 0.9868 - val_loss: 0.0274 - val
_accuracy: 0.9902
Epoch 20/25
576/576 [==============================] - 82s 142ms/step - loss: 0.0393 - accuracy: 0.9889 - val_loss: 0.0212 - val
_accuracy: 0.9951
Epoch 21/25
576/576 [==============================] - 82s 142ms/step - loss: 0.0445 - accuracy: 0.9896 - val_loss: 0.0185 - val
_accuracy: 0.9902
Epoch 22/25
576/576 [==============================] - 81s 141ms/step - loss: 0.0462 - accuracy: 0.9890 - val_loss: 0.1031 - val
_accuracy: 0.9780
Epoch 23/25
576/576 [==============================] - 82s 142ms/step - loss: 0.0475 - accuracy: 0.9890 - val_loss: 0.0274 - val
_accuracy: 0.9927
Epoch 24/25
576/576 [==============================] - 82s 142ms/step - loss: 0.0282 - accuracy: 0.9929 - val_loss: 0.0020 - val
_accuracy: 0.9976
Epoch 25/25
576/576 [==============================] - 82s 142ms/step - loss: 0.0473 - accuracy: 0.9885 - val_loss: 2.9883e-04 -
val_accuracy: 1.0000
```

Fig. 6. Dataset training in progress

```
import os
print(os.getcwd()) ##Previous Directory
os.chdir(r"C:\Users\abhay\desktop\dl\banana_ripeness_detection\data\train\overripe") ##Change with your
current working directory
print(os.getcwd())  ##Current Working Directory

for path in os.listdir():
    img = load_img(f"{path}")
    x = img_to_array(img)    # this is a Numpy array with shape (3, 150, 150)
    x = x.reshape((1,) + x.shape)
    i = 0
    for batch in datagen.flow(x, batch_size=1,
                              save_to_dir=".", save_prefix='img', save_format='jpeg'):
        i += 1
        if i > 10:     ## creates 10 image form 1 image
            break
```

Fig. 7. Image Preprocessing

Once the model is ready, the flask app can be built, which will allow us to test for the ripeness of the detection fruit (banana). We will create a flask web app using HTML and CSS. We need two buttons: one to select and another to predict. The code for the app website is written in app.py, as shown in Fig.8.

```
def predict_stage(image_data, model):
    size = (224, 224)
  # image = ImageOps.fit(image_data, size, Image.ANTIALIAS)
    image = PIL.ImageOps.fit(image_data, size, PIL.Image.ANTIALIAS)
    image_array = np.array(image)
    normalized_image_array = (image_array.astype(np.float32) / 127.0) - 1
    data = np.ndarray(shape=(1, 224, 224, 3), dtype=np.float32)
    data[0] = normalized_image_array
    preds = ""
    prediction = model.predict(data)
    if np.argmax(prediction) == 0:
        st.write(f"Overripe😩")
    elif np.argmax(prediction) == 1:
        st.write(f"ripe😀")
    else:
        st.write(f"Unripe😑")

    return prediction
```

Fig. 8. Image prediction

The previous process used the existing image that had been collected previously. New features are used to capture real-time images through the capture button. This feature used the opencv library to capture the image through a webcam device and keyboard control. The image will be stored on disk in the same directory where the app.py file is stored; refer to Fig.9 for more details.

```
if key == ord('b'):
    cv2.imwrite(filename='banana_img.jpg', img=frame)
    webcam.release()
    print("Processing image...")
    img_ = cv2.imread('banana_img.jpg', cv2.IMREAD_ANYCOLOR)

    print("Image saved!")

    break
```

Fig. 9. Capturing image in real-time

The collected data from the internet are stored on the disk; then, using the augmentation method in preprocessing, the data are duplicated/expanded by applying the desired image transformations. An example of the collected dataset is shown in Fig.10, 11 and 12.

Fig. 10. Dataset for unripe banana

Fig. 11. Dataset for ripe banana

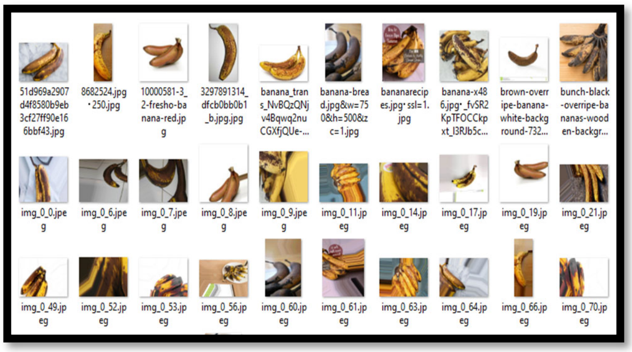
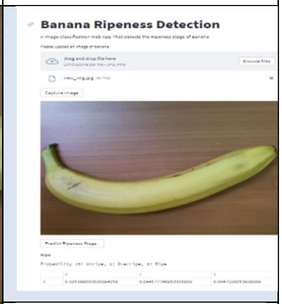
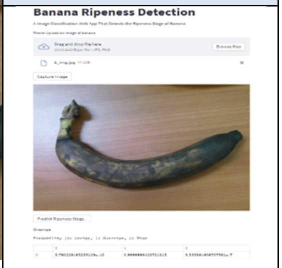


Fig. 12. Dataset for overripe Banana

We have performed a test for each category as listed in Table 1. These testing results are very promising; recognition levels reach 100% for the unripe category, 93% for the ripe category, and 99% for the overripe category.

Table 1. Sample of detection testing for three categories

Category	Image	Result
Ripe		
Overripe		
Unripe		

The testing continued by predicting the ripeness levels of the fruit shown in the ten images for each category. Table 2 and Fig.13 portray the prediction results. The unripe predictability is very high, with a score greater than 99%.

Table 2. Prediction Testing for Unripe Category

Unripe Testing			
Category			
probability	Unripe	Overripe	Ripe
image1	0.99998	8.30E-08	1.09E-04
image2	0.99999	2.31E-07	3.63E-08
image3	0.99994	5.04E-05	3.21E-08
image4	1	2.23E-18	1.10E-13
image5	1	8.71E-14	2.63E-09
image6	1	1.27E-19	2.67E-08
image7	1	9.63E-09	1.14E-08
image8	1	5.83E-29	8.23E-20
image9	0.99999	4.84E-07	5.46E-06
image10	1	6.10E-21	2.66E-16

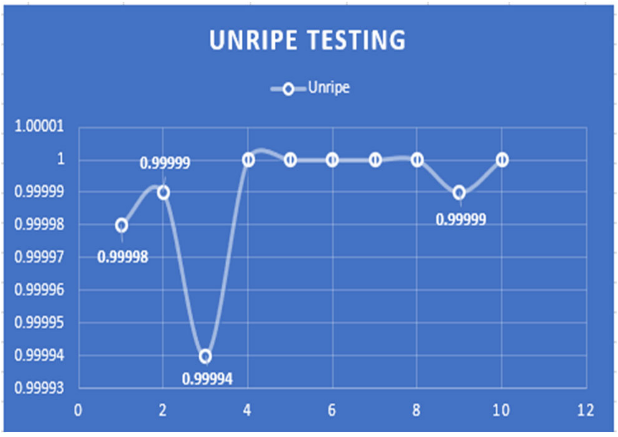


Fig. 13. Results for unripe prediction

Table 3 shows the prediction results of the ripe category for the ten selected images, and the chart of ripe prediction is described in Fig. 14. Image 6 has a low probability compared to the others, with only a 60% score, because the banana depicted in image 6 is going to ripen.

Table 3. Prediction Testing for Ripe Category

Ripe			
	Category		
Probability	**Unripe**	**Overripe**	**Ripe**
image1	0.02797	7.34E-08	0.97202
image2	0.00146	1.75E-06	0.99852
image3	0.00324	6.93E-07	0.99675
image4	0.01361	5.05E-17	0.98638
image5	0.00266	0.00006	0.99727
image6	0.00058	0.39015	0.60926
image7	6.92E-06	2.24E-05	0.99997
image8	0.08816	7.61E-05	0.91176
image9	0.11171	0.00115	0.88713
image10	0.0014	2.07E-06	0.99859

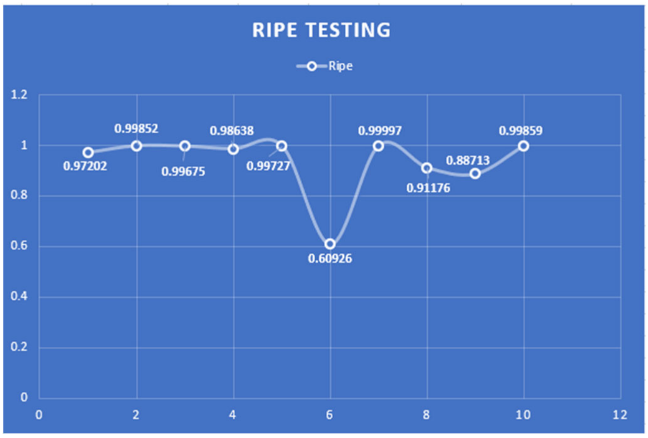


Fig. 14. Results for Ripe prediction

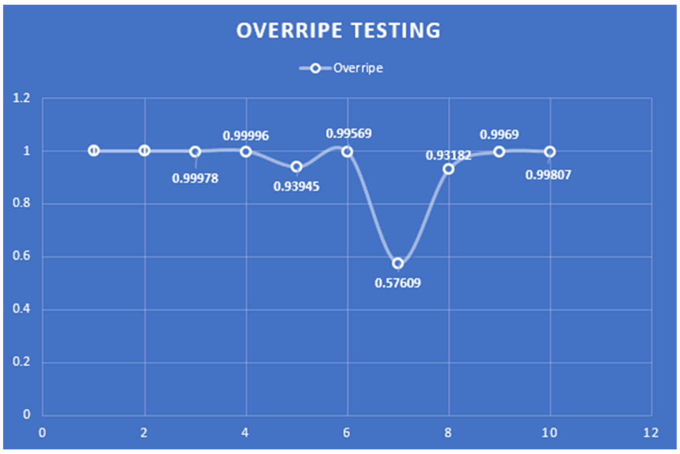


Fig. 15. Result for overripe prediction

Table 4 predicts the overripe category, and the result is also astonishing with a probability greater than 94%. This results are depicted in Fig. 15; however, image 7 has a low probability due to the background noise in the image.

Table 4. Prediction Testing for Overripe Category

Overripe			
Probability	**Category**		
	Unripe	**Overripe**	**Ripe**
image1	2.30E-13	1	5.14E-08
image2	1.97E-10	1	1.24E-08
image3	1.96E-05	0.99978	0.00019
image4	3.03E-11	0.99996	0.00003
image5	1.72E-07	0.93945	0.06054
image6	1.06E-05	0.99569	0.00429
image7	2.70E-08	0.57609	0.4239
image8	0.00042	0.93182	0.06774
image9	4.66E-11	0.9969	0.00309
image10	0.00035	0.99807	0.00156

5 Conclusion

Computer vision and deep learning approaches used for fruit ripeness verification are more manageable and accurate than many other methods currently in use. The proposed basic research was designed to solve real-life problems such as fruit ripeness detection. This project successfully trained on the dataset and generated the model. Hence, image detection based on deep learning has been successfully able to detect the ripeness of the fruit (Banana). This system also shows astonishing results with higher than 90% probability scores in classifying banana fruit images according to their ripeness. Therefore, it will be helpful to any user who needs a plan to recognize the ripeness of fruit by saving the user time and effort in choosing fruits. Future work can be extended to include other fruit datasets and to add vegetables to the dataset. The goal is to further improve the model to achieve a better probability score for each fruit image classified. We can also add many features, such as real-time fruit recognition, using images or videos.

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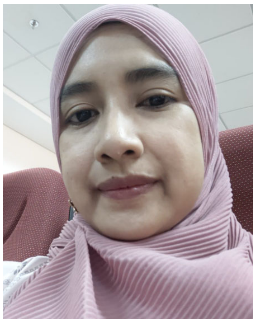
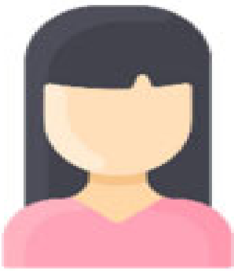


Andi Besse Firdausiah Mansur, received B.Sc(Mathematics), in 2004 and MSc(Software Engineering) in 2009. Furthermore, she obtained Ph.D. degree in Software Engineering from Universiti Teknologi Malaysia, Johor Bahru, Johor, in 2013. From 2013 to present, she is assistant professor at Faculty of Computing and Information Technology Rabigh, King Abdulaziz University. She is member of reviewer board in some international journal. Her research interest: Social Network Analysis, E-learning, Clustering, Data Mining and Mathematics

Arwa Mashat is an assistant professor in the Information System department in the Faculty of Computing and Information Technology, King Abdulaziz University, Rabigh, Saudi Arabia. Dr. Arwa received her PhD in Instructional Design & Technology from Old Dominion University in USA. Her research interests include eye tracking, education technology, online learning and internet of things.



Nouf Al-mohammadi. Received B. Sc of Computer Science from Faculty of Computing and Information Technology in Rabigh, King Abdulaziz University. Her research interests are Computer Vision and Artificial Intelligent.