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Deep Transfer Learning and Image Segmentation for Fruit Recognition

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Abstract: This paper is structured in such a way that you can able to develop the fruit recognition web app from scratch with Machine Learning & Flask. The primary objective of this research is to identify plant products in order to estimate their pricing without having to rely on recollection to enabling retail market administration and enhancing the shopping experience for customers. Methods and techniques used in this research was machine learning, deep learning, data analysis, processing, and interpretation, depending on Experimental Methods, Survey Research, Meta-Analysis, and Data Mining to provide a comprehensive and robust analysis of the data. Convolutional neural networks (CNNs) based on Deep Transfer Learning (DTL) and using previously trained weights are referred to as pre-trained networks. Pre-training, feature extraction, and fine-tuning steps of pre-trained networks involve plant product recognition. The purpose of this study is to enhance plant product packing services classification during take weight in conventional packaged vending systems. In order to assist and reduce efforts and time for customers instead of waiting while choosing fruits and vegetables that have been sold. Pre-trained ResNet50 network model that has been used in our model has an accuracy that is comparable to actual detection performance. We are using a cloud computing platform called Google Cloud Platform to deploy our model for simple and adaptable market access. This article identifies the barcode of the product accuracy up to 100 % and identifies also the type of fruits and vegetables far away from guesswork or the seller's experience by object detection. Pre-trained ResNet50 network model achieved the best results at stage fine-tuning by 100 % from the first time.

Keywords: TensorFlow, Deep transfer learning, FineTuning, OpenCV, Image segmentation, Pre-trained network

1 Introduction

Since the typical vending system relies on barcode scanning to make it easier to manage every item on the retail market [1]. Commodities are automatically identified by barcode markings. It is therefore appropriate for prepackaged products but not for Plant Product Packing Services (PPPS) that rely on weight. Long packing periods and a lack of technical assistance in the retail market are two drawbacks of plant traditional packaged vending systems [2,3]. PPPS add a barcode to plant products that do not contain a barcode after weighing while the shopper is waiting for [1,2]. The steps of PPPS begin sequentially with taking product recognition, weight, and cost computation, labeling with barcodes, and concluding with the packaging service. PPPS might be challenging to detect and comprehend, since current product management depends on traditional of circumstances, such as a) Although the plant appears to be the same and same plant species that is always changing, the classification of plants is based on descriptive categories according to shapes and a variety of colors. b) Intuitively is based on guesswork. c) Opinion relies on experience. d) Using human memory to sort and retrieve each item's barcode, which leads to inaccurate categorization [4,5]. This method of managing the product makes jobs more difficult, which makes them more likely to have tight margins for error. It also makes data deletion more expensive and time-consuming for a retailer. With the present PPPS, consumers confront challenges, such as 1) there is no trust in the retailer's estimation of the product's price being accurate. 2) Customers are under more and more time pressure [6].

The term shopping experience in this study refers to a consumer's perception of a retail market and the retailers (providers) perception on our model [7]. It produces an augmented reality that enables retailers (providers) and consumers (shoppers) to collaborate intelligently for their mutual benefit [4,8]. Shopping productivity is defined as

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the capacity to reduce time and effort, make informed purchases, save money, and enjoy shopping [1,8]. Our model contribution for maximizing shopping productivity and understanding of consumer wants are as follows: a) Gaining consumer satisfaction confirms his go back to the retail market. b) Service quality which raises productivity, sales and generates profits in the retail market. c) Strong driver for adopting upgrades to technology infrastructure [9]. This system provides support to all stakeholders to facilitate the management of the retail market and improve the shopping experience of consumers, a) Retailer assistance in transforming the shopping experience it more pleasurable through improve customer service. b) Consumers benefit where allows them to make purchases without feeling pressured time [8].

2 Methodology

In this paper, computer vision technologies are used to classify plant product before packing services. The workflow in this study is broken down into two sections: workflow for deep learning and technical management.

2.1 Workflow for Deep Learning

In order to develop the architecture we needed for real-time fruit testing and recognition, it is separated as follows: 1) Client-side which includes Python libraries and is keras and tensorflow 2.0. Create a pre-trained ResNet50 network model for data analysis. The workflow of the Pre-trained ResNet50 network model for deep learning architecture, plant product recognition and training capability, is as follows: a) pre-training b) feature extraction. c) Fine-tuning on the entire model (Unfreezing). d) Images were scaled or resized to fit a neural network. Once our machine learning model is complete, we will move on to the deployment side. 2) Server-Side uses the Google Cloud Platform and Flask. Using Flask, a web server is created by rendering HTML, CSS, and Bootstrap on both the frontend and the backend. The plant product recognition model deployment workflow, through by using our website from within the retail market. The four volunteers were picked at random to assess the thirteen items that were purchased before packaging service. 3) The workflow of preparing the fruits and vegetables images, which came from a variety of sources, as following: a) For our own dataset, we gathered a collection of 55808 images from five retail market in Jordan between July 26 and August 28, 2022. b) Online public datasets include the Fruits-360 open-source dataset from Kaggle and GitHub. You can access its 131 items and 91758 pictures by clicking on the references links [10,11,12].c) In order to gain a deeper understanding, the process of cross-validation involves dividing a dataset into training, testing, and validation datasets. The entire dataset which is 131 products were distributed in 51 layers as follows: Training set size: 67692 images, Validation set size: 53598 images and Test set size: 26276 images belonging to 131 classes.

2.2 Workflow for Technical Management

A workflow for managing our model for plant product packaging services, are as follows: First) take the item's weight product. Second) real-time identification of the item on the pan using deep learning techniques. Third) after detecting the product, the system displays information and recommendations regarding the items. Output will be a confidence score indicating the three items with the highest probabilities out of 131. Fourth) the provider must confirm the information without relying on memory. Fifth) after receiving confirmation, the system calculates expenses, prints a label with the relevant barcode, and completes the packing service.

3 Build Machine Learning

3.1 OpenCV

A color image is a combination of three channels, commonly referred to as RGB, or Red, Green, and Blue [13]. As shown in Figure 1, we use Python libraries in this paper to comprehend how to process images and detect objects. OpenCV (Open-Source Computer Vision), Matplotlib RGB, and Pillow RGB libraries are among those that use more contemporary Python and offer more sophisticated capabilities. Matplotlib and Pillow are out performed by the OpenCV library in terms of speed and power when processing images [14].

Barcodes are a method of identifying products that are composed of parallel lines that are organized by black and white bars. The process of scanning the barcode to get a string of codes composed of bars of different widths and colors. Currently our code supports EAN-13 encoding methods. The UPC-A standard is the foundation for the EAN-13 barcode, which the International Item Coding Association first used in Europe before progressively spreading around the globe [15].

In this study, on December 10, 2022, we bought a pineapple product from a retail market in order to use OpenCv to detect its barcode. Enter the barcode twice to read it and we were able to detect the barcode: 2162813005905. The first time, we input the image as it is, as shown in Figure 2 (a, b). The second time, we removed the description of the barcode, which is the decimal number below the barcode, as shown in Figure 2 (c, d).

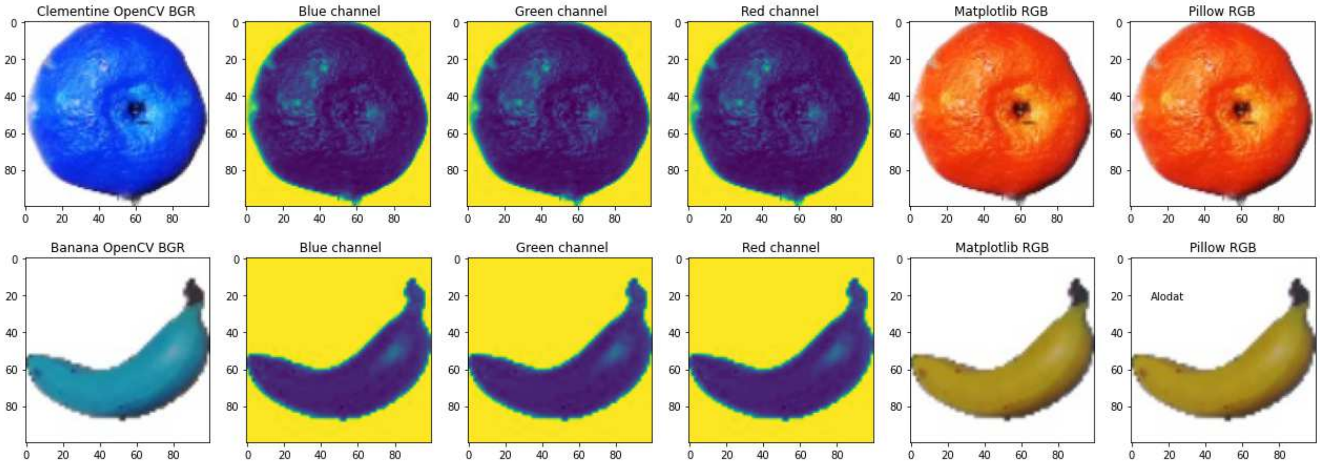
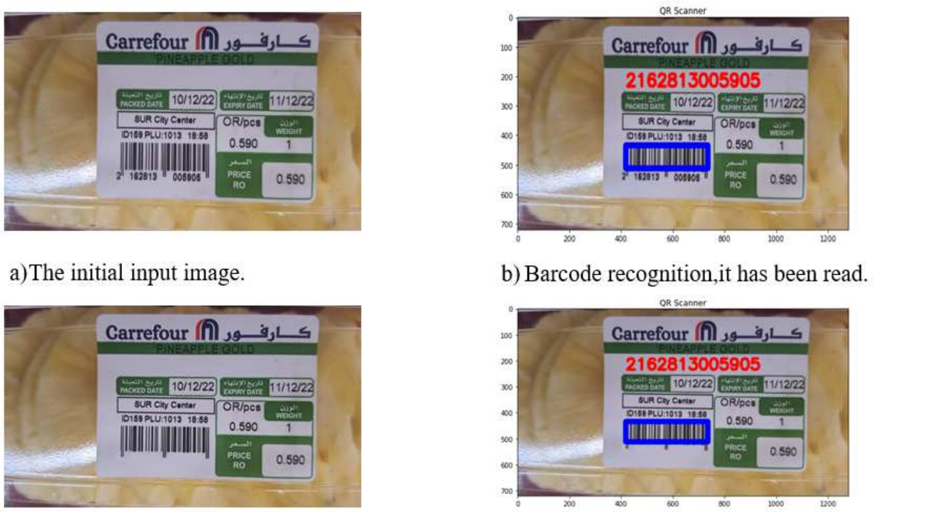


Fig. 1: A variety of products for visualizing.



a) The initial input image.

b) Barcode recognition,it has been read.

c) Remove barcode description from input image

d) Barcode recognition after remove description.

Fig. 2: Barcode reading using OpenCv.

3.2 Transfer Learning

CNN includes parameters in this study to improve recognition accuracy. Internal layers are feature transforms (body), as well as classifier (head). The feature transforms (body) is split into the following sections: a) Convolution layers use 3x3 filters (kernel, Feature detector) can be applied to images and generates Feature Map (activation map). Activations map (feature map) is produced by applying the same filter on all parts input image. The multiplication is performed between an array of input image 32X32 and filters (kernel, Feature detector) is a two-dimensional array of weights 3x3. Activation function for the rectifier (ReLU), which allows only positive values and sets all negative values to zero. b) Pooling layer to reduce the size of the image even more, and produces a pooled Feature Map, which is referred to as the bottleneck layer. The classifier (head) is split into the following sections: a) The 4,096 neurons in the flattening layer, which is generated by the fully connected-layer, which connects to the body and the head. The gradient descent optimizer's learning rate was set at 0.001, meanly average number of jumps. This study's last layer of full connection contains a Soft-Max classifier, and 131 neurons. Each box in this Figure 3 represents a layer in our design and the function that layer carries out.

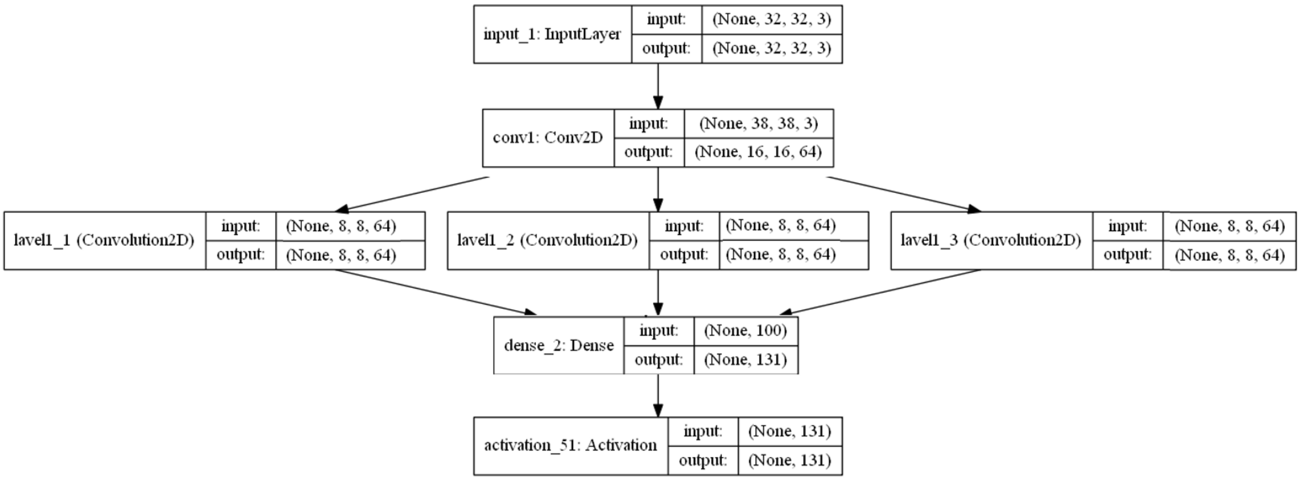


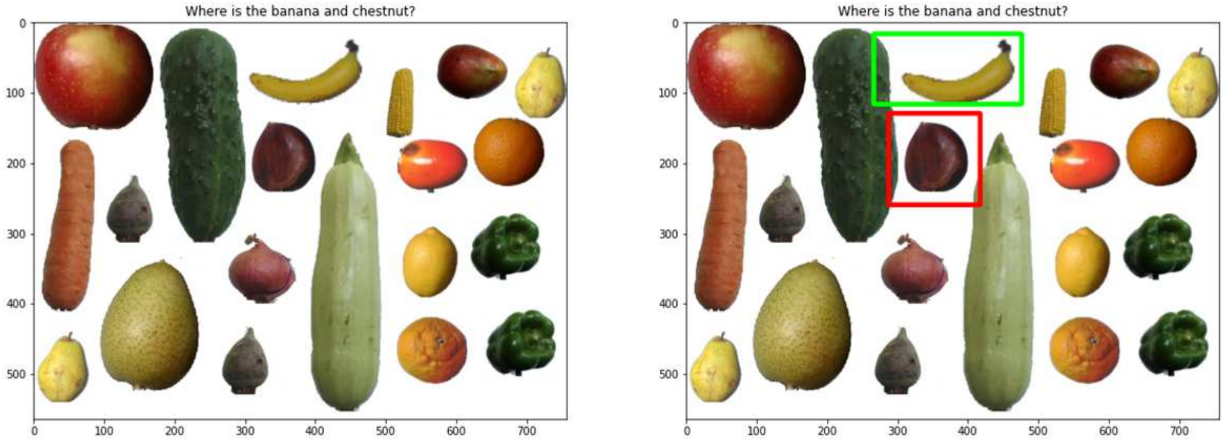
Fig. 3: 51-layer architecture built on a Pre-trained ResNet50 Network Model

Researchers have helped us by releasing their code as seen in the ImageNet team's efforts to test picture identification, called Deep Transfer Learning (DTL) [2, 16, 17]. DTL open-source models are used on a data set that it has never seen before as part of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The following justifies the use of DTL in computer vision: a) avoids having to retrain the network from scratch, which expedites training, and increases precision. c) CNN requires more time and a huge dataset, whereas, DTL deals with small data sets. In this paper, we utilize previously learned feature maps (weights trained) in the Pre-trained ResNet50 network model to make it easier to identify plant products. The following procedures would be taken to construct the Pre-trained ResNet50 network model with CNN networks: The first step a) Pre-trained phase use for images has a width of 75x and a height of 3 in 75x channels. b) Using pre-loaded weights from ImageNet for training (by setting weights='imagenet'). c) With the exception of the final two layers of the classifier (head), the flattening layer and the Softmax classifier, all 50 classes will stay constant (by setting layer.trainable=False). d) The pre-trained networks (by setting include top=False) that the last layer is removed. The second step: Feature Extractor phase, it extracts from the last two layers only, which involves freezing the bottleneck layer and retraining on head (by setting the model.trainable = False). The third step: fine-tuning phase is unfreezing the Pre-trained ResNet50 network model and using trained layers with updated weights in the top layers (by setting model.trainable = True).

3.3 Computer Vision

The goal of computer vision is to give computers or software the ability to comprehend what is seen in images. Computer vision used many tasks before reaching segmentation one of these tasks is called image classification. The purpose of image classification is to determine if a fruit is present in the image or not, as shown in figure 4 (a). The image would be the input, and the output would be a confidence score, which is a value between 0 and 1. The confidence score indicates in our scenario the probability of having a particular fruit item out of 131 fruits. The task of image classification will be followed by image classification plus location in computer vision, which called object detection task. In this task, the ability to determine the X and Y coordinates of the top left corner of a box that surrounds the fruit, which is referred to as the bounding box, as shown in figure 4 (b). The object detection task uses bounding boxes to find the fruit in the image and each bounding box has a confidence score. Object detection is getting the coordinates of the location of the fruit in the image, which is a small extension of the image classification task. The process in the OpenCV to be extracted all significant elements from an image, giving us the capacity to identify shapes, also known as contours. Contours can be continuous lines or curves that surround the whole perimeter of an object in image. We receive two arguments from OpenCV: contours and hierarchy. The array of (x, y) points that make up the contour are saved as the variable Contours. While the parent-child interactions contours are described by hierarchy [18].

The purpose of the detection algorithm task Single-Shot Detector (SSD) in computer vision is classification, and move from object localization to object detection. SSD uses one or more bounding boxes, depends on Transformer, and shares many techniques with the well-known algorithm YOLO. In order to create feature maps, the SSD first takes an image as input and runs it through a convolutional neural network or a



a) The Original image b) The object detection task with bounding boxes

Fig. 4: Image classification plus location bounding box.

backbone. Following, we have a number of convolutional layers where we are gradually shrinking the output volumes. After that, we attempt to detect things using the generated feature maps [19].

We looking at much bigger and much more complex systems that and first of these systems is object detection in algorithm called SSD. SSD is a genuine milestone in object detection because it is both faster and more accurate than the previous state of the art, as shown in figure 5 .

3.4 Image Segmentation

We turn to image segmentation because traditional computer vision is inaccurate, sluggish, impossible to achieve and not generalizable enough. Following object recognition in computer vision, Image segmentation is the next very difficult task. They are the ability to specify the pixel in the bounding box that represents the fruit in an image without a background and realize any kind of fruits. Image segmentation determine where the fruit is in the image and can be split into two types 1) semantic segmentation predict whether the different pixels inside your image belong to same item. Semantic segmentation tells us which pixels belong to a fruit and only provides a maximum of three different pixels. 2) Instance segmentation is the ability to distinguish between different clusters of pixel, where each clusters of pixel in the image is classified into standalone cluster [20,21]. While semantic segmentation disregards object instances, instance segmentation divides objects of the same cluster into distinct segments. The Contour Detection is a useful tool for detect the borders of objects, shape analysis and object detection. Using contours is one approach that can be used to perform segmentation. Contour refers to boundary pixels that have the same color and intensity, as shown in figure 6.

Shi's (2016) model, called ESPCN (Efficient Sub-Pixel CNN), reconstructs a high-resolution version of an image from a low-resolution version. It makes use of effective "sub-pixel convolution" layers, which can be used to learn different image upscaling filters.

4 Deployment Model

Deployment model is a visual web interface and we will be used TensorFlow 2.10.0 serving in Python and the Flask web 2.0.3 framework, to deploy a pre-trained ResNet50 network model. Making advantage of our deployment model to the plant product recognition, which will serve to get predictions as following: a) technically, it straightforward to maintain and upgrade the model over time in a retail market environment. b) Our models are available on the retail market for use by retailers (providers). Cloud computing is more efficient, provides access to greater storage, and does not require installation on your local machine. The Google cloud platform, a cloud computing platform, is utilized in this paper. The platform integrates with Google Cloud services to facilitate machine learning framework like training. For this purpose, we create a web site dedicated for pre-trained ResNet50 network model, for more details you can visit our web site [22].

5 Result and Discussion

5.1 Performance Assessment

As demonstrated in Table 1, after fine-tuning, the pre-trained ResNet50 network model achieves 0.999236

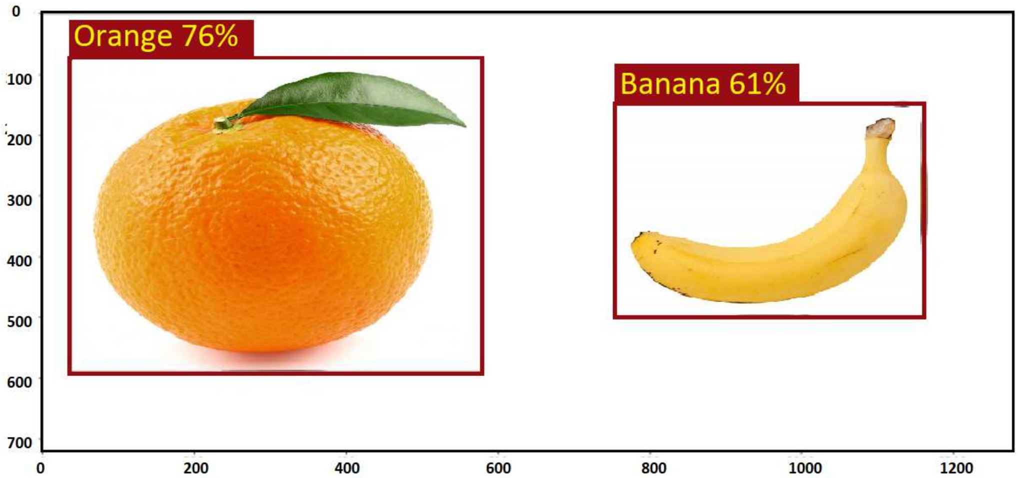


Fig. 5: Predictions at each items

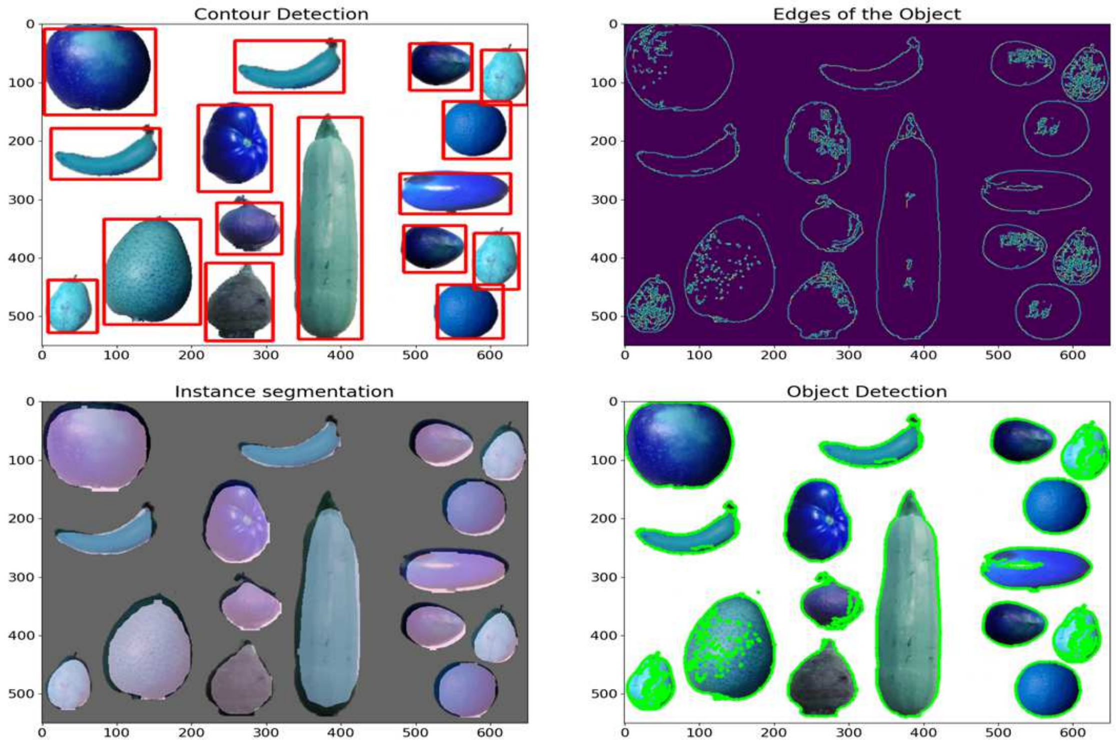


Fig. 6: Predictions at each items

% and 0.997185 % accuracy on the training and validation set. We note the first Pre-trained stage the worst, as it turns out that 0.0125 % accuracy on the training. On the test set, in our ResNet50 model the second Feature Extractor stage which is called freezing achieves 0.987929 % percent accuracy, but only 0.0000001 on the validation set in the first Pre-trained stage. It takes much less time, as the training lasted for more than two days, compared to the third stage, which took approximately two hours.

To test the performance, objective metrics were used like precision, recall, accuracy, and F1-score. The accuracy of the ResNet50 model has the worst first-stage performance, with an accuracy of 0.006903 correct

Table 1: Accurate performance of deep learning transfer

Perfor of ResNet50		accuracy	loss	Time in Hour
Pre-trained	Train	0.01250	4.934	51:18:05
	Valid	0.0000	4.898	
	Test	0.000000	4.898	
Feature	Train	0.998854	0.002	1:49:47
	Valid	0.9895515	0.021	
	Test	0.9879294	0.037	
Fine-Tuning	Train	0.9992365	0.002	1:48:34
	Valid	0.99718511	0.007	
	Test	0.997089	0.011	

Table 2: Comparison of a performance ResNet50 model

Confusion Matrix	ResNet50			
	Accuracy	precision	recall	f1-score
Pre-trained	0.006903	0.000053	0.007634	0.000105
Feature Extractor	0.858166	0.890492	0.848014	0.845562
Fine-Tuning	0.868473	0.889592	0.846612	0.837313

predictions, as shown in Table 2. The Feature Extractor and Fine-Tuning have the best accuracy, with a precision of 0.890492 and 0.889592 respectively. On the ResNet50 model, an average precision of 0.889592 percent was achieved, a recall of 0.846612 percent, and an F1 score of 0.837313 percent. In terms of classifying plant items packing services, the ResNet50 model surpasses the other pre-trained networks models.

In accordance with the box and whisker plot, 50 % of the precision have scores of 97 points. Additionally, as shown in figure 7 a, 25 % of the precision results have results above 85 points, 50 % have precision results of 97 points, 75 % earned 100 points, and the standard deviation (std) is 0.157. The distribution of data, including its frequency and volume, is represented by the histogram. We collected 131 products for our model, with quantity of data connected to validation data and frequency of data related to precision. The number of frequencies that fall under the precision category is represented on the y-axis. The x-axis displays the precision range, and the height of each bar displays the frequency within that range. The dataset median is 0.97, the 10th bin ranges from 0.97 to 1.00, and the count exceeds 73/131 for that category. Additionally, as seen in figure 7 b, this can highlight any gaps or outliers in the data set.

The freezing phase of the ResNet50 model as well as learning curves for training and validation/loss accuracy, as shown in figure 8.

Evaluation results of the ResNet50 model in Fine-Tuning stage from pre-trained networks, using the Confusion Matrix performance of validation data. The number of correct predictions is represented by the diagonal elements, whereas the number of incorrect predictions is represented by the other elements. Area under the Curve (AUC), provides a summary of the diagnostic accuracy. AUC equals 1.0, which indicates that the ROC curve has perfect accuracy. If the estimated AUC is less than 0.5, the test performs worse; if it is greater than 0.5, the test performs almost perfectly. We utilize a curve connected with validation data called The Receiving Operating Characteristics (ROC) for the best and worst ResNet50 models, respectively, to validate the ability to classify items' packaging service, as shown in figure 9.

We were able to display a vertical line using cross-validation learning curves in the last levels of fine-tuning. Figure 10 displays a vertical line to further illustrate how effectively the model was learning.

5.2 Classify Before Packaging Service

Plant product recognition model was utilized Pre-trained ResNet50 network model with fine-tuning phase. Four volunteers at the retail market were tasked with examine their merchandise which are thirteen items, and determine which were bought before the packaging service. Our model was still able to recognize each commodity and match The Actual Item for all shoppers despite the fact that the proportions vary. Lemon Meyer had the lowest percentage of the commodity, estimated at 0.39036, and the highest percentage was for the Pineapple Mini commodity, estimated at 0.99948. Figure 11 was taken from the website that was published for the retail market. PSNR of low resolution image and high resolution image is 23.2646, PSNR of predict and high resolution is 24.4465. Improving the resolution of images with JPEG compression, as shown in figure 12 .

6 Conclusion

Artificial intelligence tools were used to identify the type of fruits or vegetables, weight and price by placing the correct and appropriate barcode marks, far away from guesswork or the seller's experience. The researchers modified the code of OpenCV to know the barcode of the product through, firstly, reading the image (black lines and decimal numbers), and secondly, through black lines only without decimal numbers, the result was 100 % right. This study able to determine the objects (fruits and vegetables), by drawing bounding boxes around it with mention their names and percentage for each one. The study also able to determine the objects itself without drawing boxes around it, instead of that Contour Detection used and it is a useful tool for detect the borders of objects, shape analysis and object detection. We build a web site visual web interface to deploy a pre-trained ResNet50 network model, this web site will useful for plant product recognition, it straightforward maintain and upgrade the model over time in a retail market environment. Pre-Trained ResNet50 model with 51 layers achieved best results at stage feature extractor and stage fine tuning according time, efforts, and accuracy, also, the

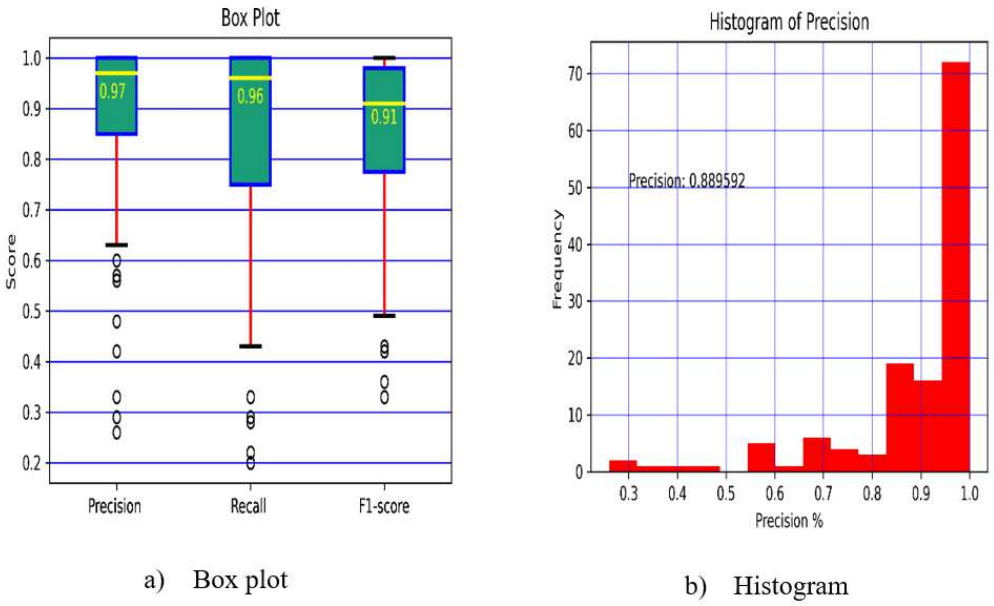


Fig. 7: Precision fine tuning in validation data.

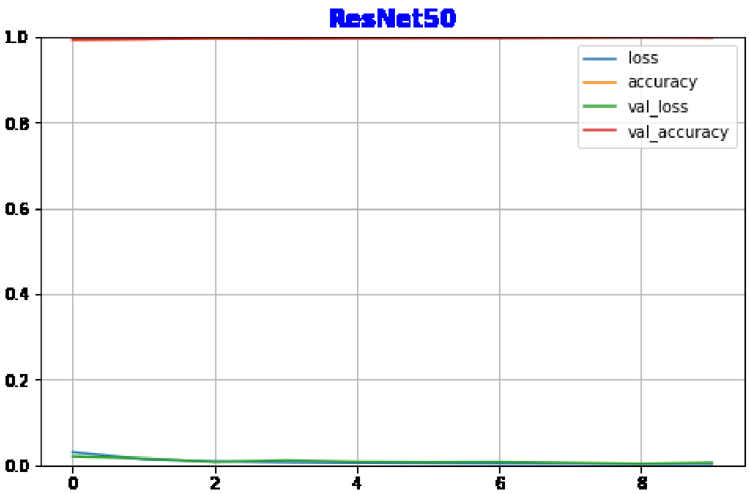


Fig. 8: Loss and Accuracy Curves.

model achieved the best results with same stages according accuracy, precision, recall, and f1-score. Our model Pre-Trained ResNet50 with 51 layers was still able to recognize each commodity and match The Actual Item for all shoppers despite the fact that the proportions vary, so that the model was able to identify the types of fruits and vegetables by 100 % from the first time.

7 Compliance with Ethical Standards

The four volunteers were picked at random from within the retail market to assess the thirteen items that were purchased by the customers before packaging service. the participants were fully informed about the study's objectives and methodologies, have the option to participate voluntarily, and accept a written consent form before any data is collected from them. This is a crucial ethical consideration in this research to protect the rights and welfare of study participants, including anonymity and safety of data, non-discrimination, and respect for

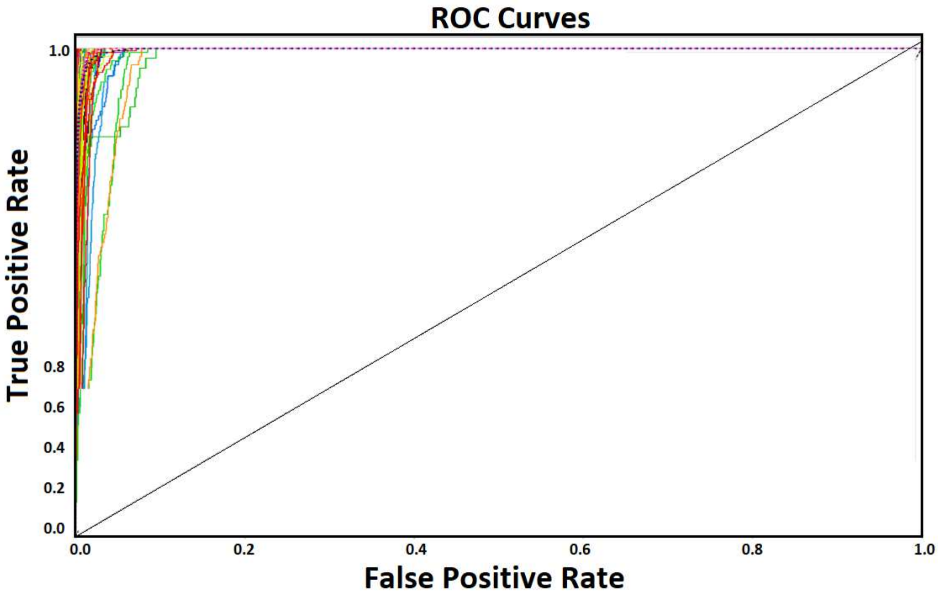


Fig. 9: The Receiving Operating Characteristics (ROC).

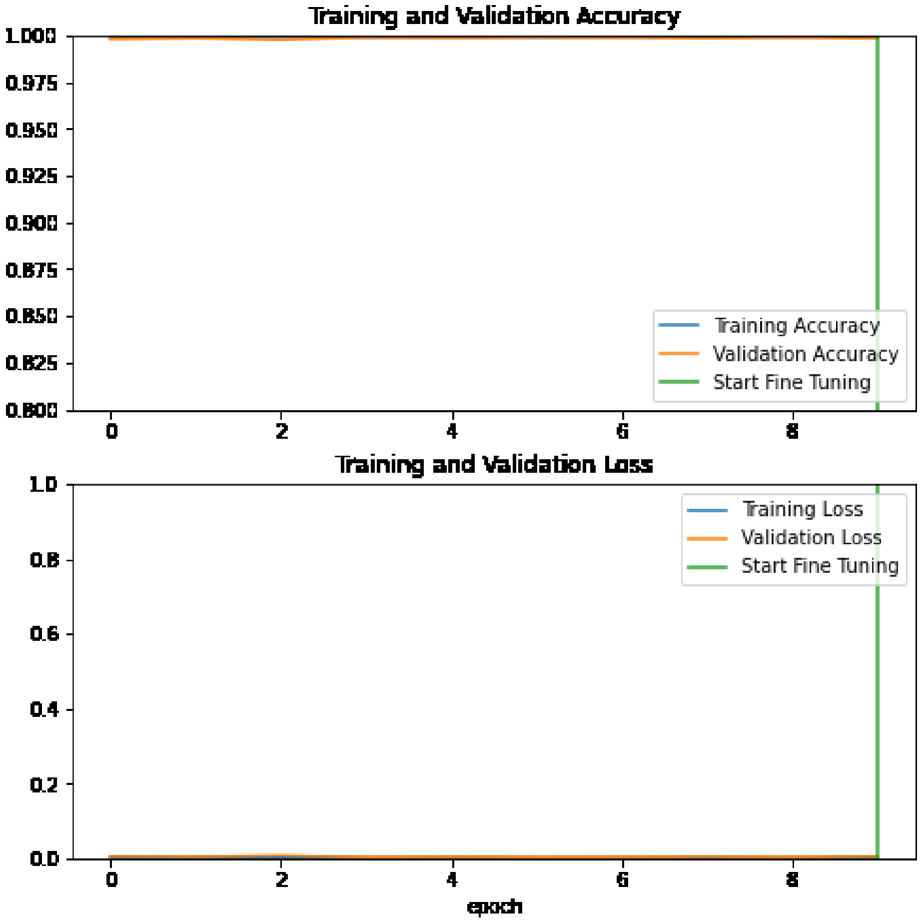
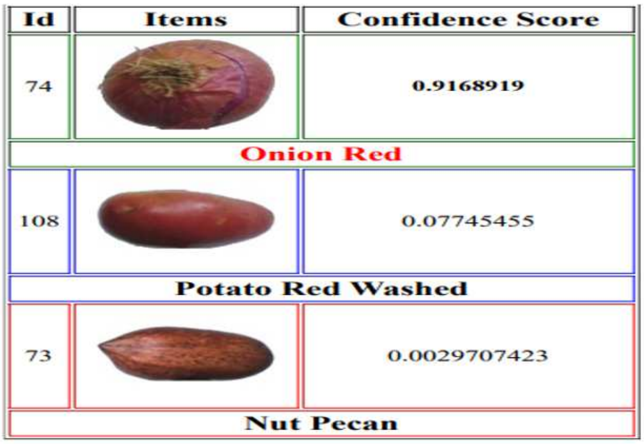


Fig. 10: The Vertical Line of Fine-Tuning.



Id	Items	Confidence Score
74		0.9168919
Onion Red		
108		0.07745455
Potato Red Washed		
73		0.0029707423
Nut Pecan		

Fig. 11: Before the packaging service, Onion Red product recognition.

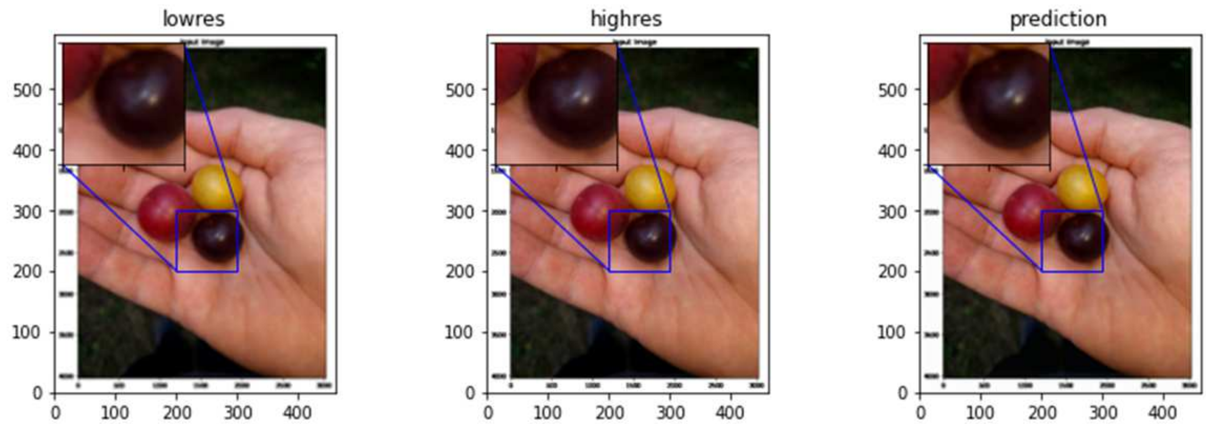


Fig. 12: Predict, low and high resolution.

privacy and confidentiality. Additionally, provide responses that are based on factual information, no conflict of interest and do not promote or endorse any unethical behavior or practices.

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Mohammad Alodat earned his B.A. in Computer Science at Irbid National University in 2005, and from the college of engineering went on his Master degree and Ph.D. in Computer and Information Science from the University of Craiova Computers and Electronics in 2015. He worked in secondary schools at the Jordanian Ministry of Education in 2008 with the rank of teacher. He taught since 2016 to 2023 in the Sultanate of Oman at the Sur University College and Jadara University in the Department of Information Technology with the rank of Assistant Professor. he researching Deep Learning and Artificial Intelligence related to Neural Networks, Convolutional Neural Networks with TensorFlow 2.0 and OpenCV. He Touched on the topics of Face Detection and Recognition, Medical Imaging, Transfer Learning and CNN Visualization, Web Design: Flask, R Programming for Statistics and Data Science, and Robot Operating System (ROS). He worked Programmer in Jordanian Ministry of Defense and the Department of Information Technology in Sur University College in Oman. His volunteer work in community service by conducting machine learning and deep learning courses in the Hashemite Kingdom of Jordan in the city of Irbid in the Hatem Cooperative Society and in the Sultanate of Oman in the city of Sur.