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Recognition of Fruit Grading Based on Deep Learning Technique

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Abstract

Fruits, with their delightful taste and rich nutrient content, play a crucial role in human health. Their classification is vital in agriculture and influences pricing in supermarkets. Efficient fruit detection is critical for import or export due to physical environmental effect. This project implements the deep learning technique of YOLOv5s and YOLOv8n models to classify fresh and rotten fruits. Besides that, there are two classes as fresh and rotten for grading three fruit varieties involved such as apples, bananas, and oranges. The 600 sample images are collected from Kaggle and annotated using the Roboflow software. Overall, the result of the proposed project is evaluated using the metric mean Average Precision (mAP). The mAP of YOLOv5 is 98.99% and YOLOv8 is 99.36%. Hence it proves YOLOv8 model performs better is in its identify and classification of the fruit grading.

1. Introduction

Ensuring sufficient nutrition is crucial for maintaining good health, as is focusing on development and damage compensation. Fruit consumption is how most people obtain their nutrition and maintain their health. Eating a diet high in fruits will lower the risk of diabetes, cancer, heart disease, and inflammation respectively. The new processing techniques and cutting-edge computer vision technology have been made possible by the development of artificial intelligence in many fields in this current era [1][2]. Additionally, there are continually looking at new agricultural technology trends. Agriculture is one of the demanding sectors of a country contribution and it more increasingly becoming as intelligent agriculture gains popularity and yield strong results [3]. Consumer are unable to tell whether the fruits they purchase are rotten or fresh. Even so, they are unable to see the early stages of disease or whether the fruits have contracted the virus if they are sold without a plastic or box. Moreover, the supplier will experience a financial loss if the consumer does not select the rotted fruits since they will not be able to identify the flaw in time. Because so many fruits arrive at their factory unprocessed before being sold in stores, suppliers occasionally neglect to check the quality of each fruit. In addition to fresh fruit import and export, rotting fruit inspection and quality degradation pose a serious challenge to the food processing industry. Because of this, selecting and grading fruits of superior quality calls for a skillful and efficient method.

This paper attempts to show that an automatic and efficient artificial intelligence detection method based on lettuce dataset. So far, however, there has been little discussion about detection for the lettuce grown. Hence, the deep learning model provide valuable information for agriculture sector, and it also help the farmer to manage cultivate crops effectively.

2. Methodology

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The proposed system consists of multiple steps, as shown in Fig. 1. To begin with, fruit images are gathered from Kaggle training evaluation. The images are then annotated using the Roboflow software and pre-processing step is used to enhance visualization in the processes that follow. The annotated dataset images are trained in YOLOv5 and YOLOv8 models. The refined models yield performance metrics that are validated, and evaluation outcomes are obtained. Finally, a comparative analysis is conducted to ascertain the deep learning models' accuracy metrics

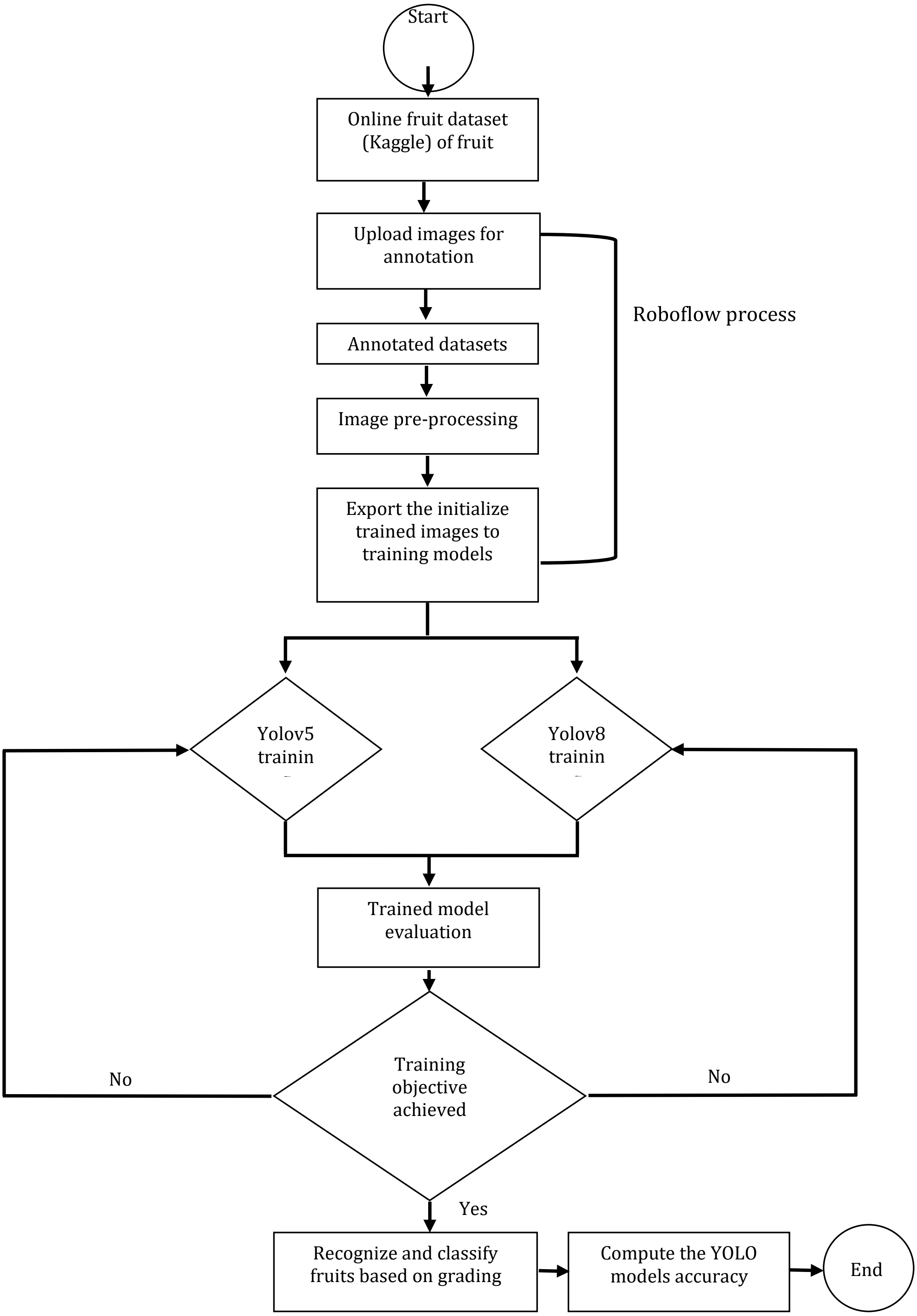


Fig. 1 *Flowchart of proposed project*

2.1 Data Collection

For this proposed project, the selected fruits images are apple, banana, and orange that were obtained from Kaggle online dataset as it contained 600 images in total. Each type of fruit was divided into classes as fresh and rotten classes. The dataset for categorizing fruits is accessible to the public for future research. The classification of fruit grading datasets is presented in Table 1.

Table 1 *Fruit datasets*

Fruits	Fresh	Rotten
Apple	100	100
Orange	100	100
Banana	100	100

2.2 Roboflow software

Roboflow is a deep learning tool that enable computer vision tasks easier and simpler whereas it enables developers are excessed to create computer vision applications regardless of their level of expertise or experience. Both object detection and classification models are supported. Before exporting the Roboflow to training models, it goes through three steps shown in Fig. 2. The first step is to label the images according to it classes. Follow up, the images will undergo pre-processing to raise the image quality and get and effective training result.

Fig. 2 *Flowchart of annotation in Roboflow*

2.2.1 Image annotation

In this project the fruit images are annotated with bounding box tool shown in Fig. 3 with the method of object detection to locate object within the image and are separated to different classes as fresh and rotten.

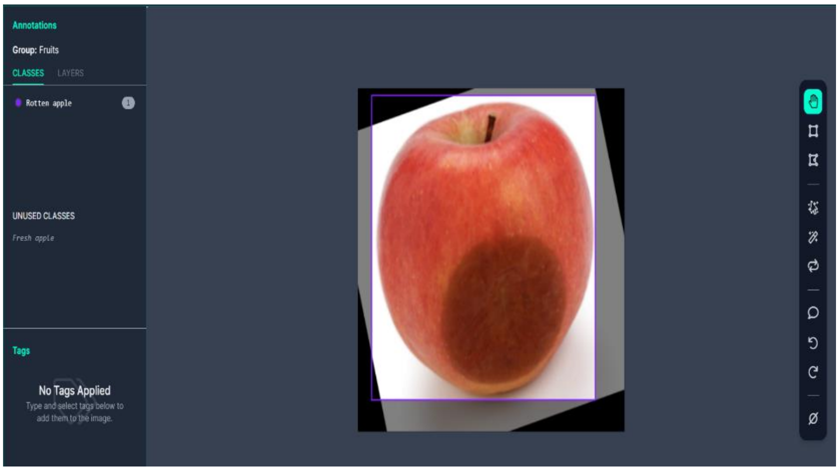


Fig. 3 *Flowchart of annotation in Roboflow*

2.2.2 Image Pre-processing

Before fitting the model, the images will be pre-processed to get good training, validation, and testing results and to avoid overfitting the model. In Fig. 4 illustrates the pre-processing of the dataset images, the images are auto orient and resized it to 640×640 pixels.

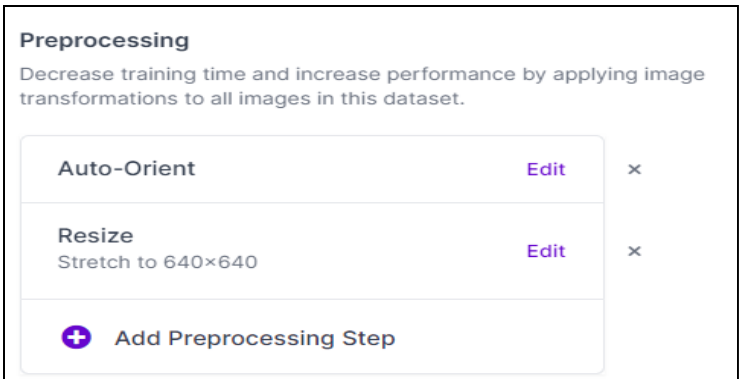


Fig. 4 *Pre-processing of images*

2.2.3 Training Datasets

In deep learning technique to train or fit is the largest subset of the original dataset is called training data. In the Roboflow, once completing the annotation process, it creates as dataset by dividing the annotated images into train, validation, and test sets. So, form the Fig. 5 the training model is set to ratio 70:20:10.

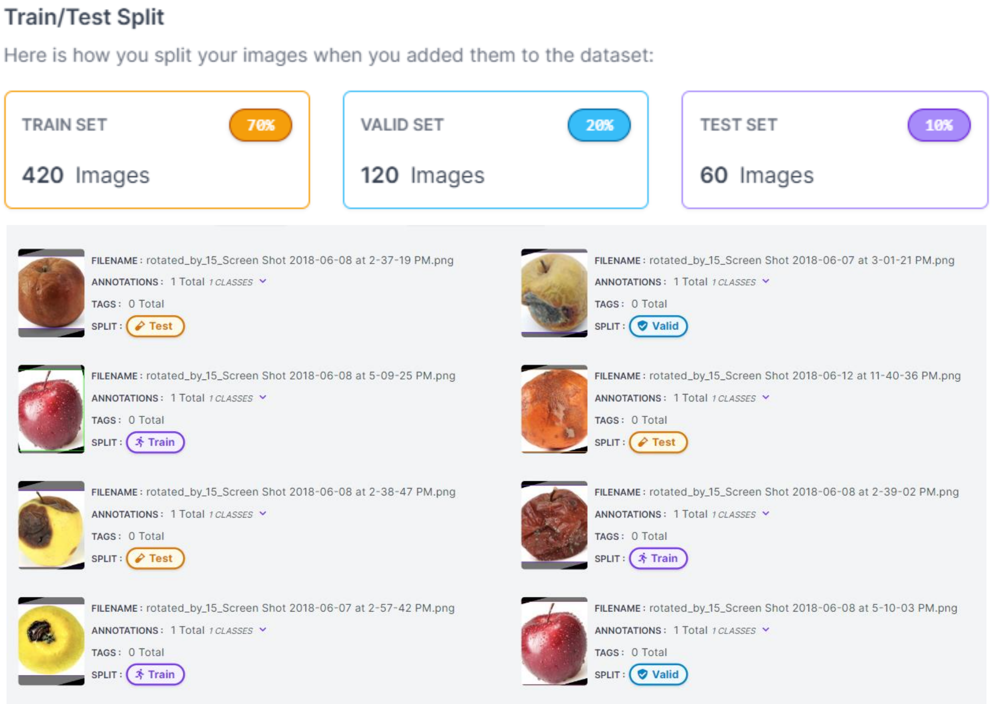


Fig. 5 *Train, test split images for training*

2.2.4 Performance Metrics of YOLO Models

For the quantitative evaluation, three performance metrics are selected which are precision (P), recall (R) and mean average precision (mAP) for each trained YOLO models as calculated in Eqs. 1,2 and 3.

$$\text{mAp} = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

where *TP* is the number of true positives, *FP* is the number of false positives, *TN* is the number of true negatives, *FN* is the number of false negatives, n is the number of thresholds and AP_k is the average precision of class k.

3. Results and Discussion

3.1 Roboflow Training Datasets Results

Training results obtained from the Roboflow shows that mAp is 99.2% as it shows that good overall performance at different confidence levels. The precision is 97.9% that shows that the model has a low rate of false positives and is very accurate when predicting an object which is the fruit classification whereas the recall is 95.4% shows that a high percentage of instances of the target class are successfully captured by the model, with a low rate of false negatives. Fig. 6 show the performance of metric graphs of the datasets.

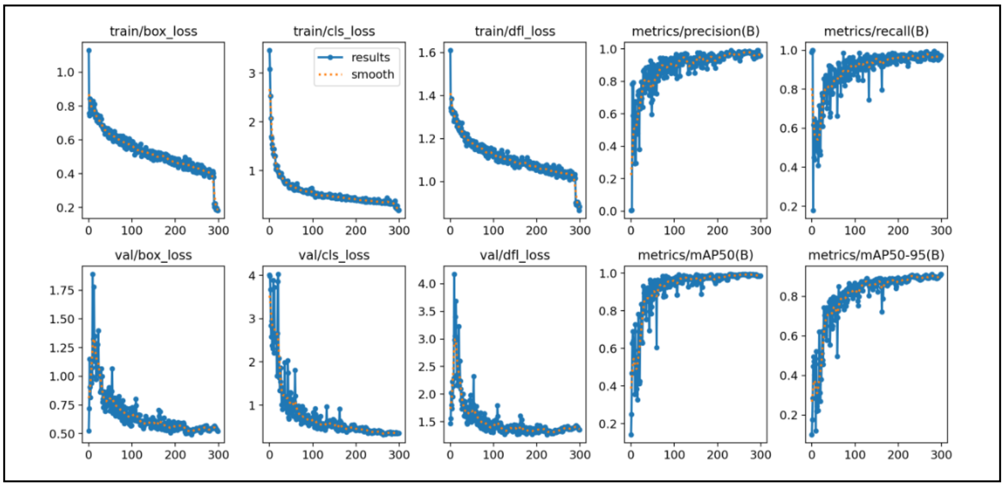


Fig. 6 *Performance metrices graphs of Roboflow*

3.2 YOLO Models Result

YOLOv5 and YOLOv8 model was trained and tested on the fruit dataset. To train the model, the image resolution of 640×640 pixels was used. Therefore, the best models and good performance on the fruit dataset able to obtain after the model training.

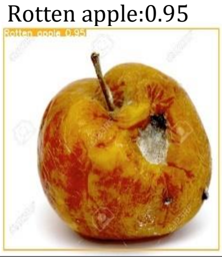
From Table 2 both YOLOv5s and YOLOv8n models compute well, exhibiting high mean Average Precision (mAP) scores that indicate robust object detection capabilities. In terms of mAP_0.5 and precision over all epochs, YOLOv8n shows a slight advantage over YOLOv5s, potraying a better ability to locate objects precisely. However, YOLOv8n performs highly in recall, especially until 200 epochs, indicating a greater capacity to capture a greater percentage of relevant objects. However, YOLOv8n requires more training time, likely attributed to its larger architecture than YOLOv5s

Table 2 *Performance metrics for different hyperparameter*

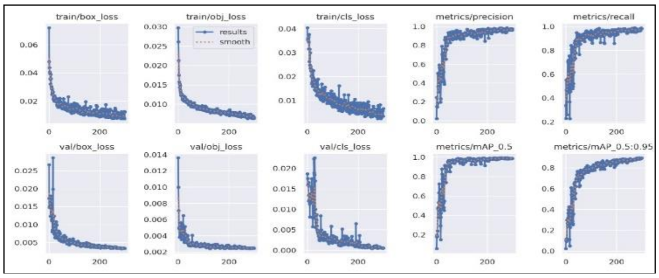
Models	Epochs	mAP_0.5	mAP_0.5-0.95	Precision	Recall	Training time (min)
	100	0.9868	0.8516	0.9477	0.9666	13.97
YOLOv5s	200	**0.9899**	0.8727	0.9583	0.9819	28.02
	300	0.9859	**0.8934**	**0.9757**	**0.9821**	43.02
	100	0.9906	0.8996	0.9573	0.9757	17.09
YOLOv8n	200	0.9899	**0.9205**	0.9353	**0.9967**	34.71
	300	**0.9936**	0.9085	**0.9785**	0.9753	42.20

Table 3 shows the confidence score of the fruits obtained are different according to the YOLO model.YOLov5 shows the lowest confidence score than YOLOv8 due to reason YOLOv5 need more epoch iteration training to get a higher confindece score. This difference can be explained by the fact that YOLOv5 needs more training epoch iterations in order to obtain a confidence score that is either comparable or higher. Longer training iterations are necessary, which implies that YOLOv5 may need more fine-tuning to distinguish and classify fruits correctly. This could affect its confidence scores during the early training stages.

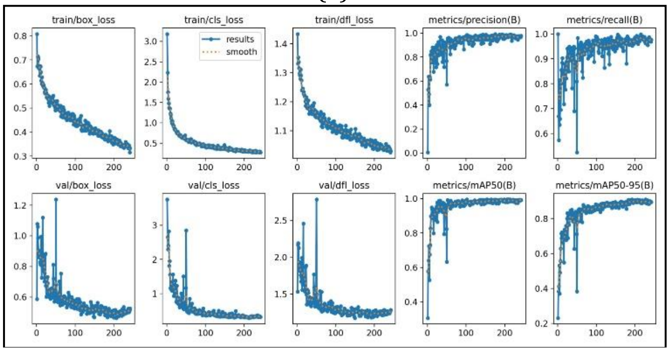
Table 3 *Testing results for fruit recognition and classification of YOLO models*

Models	Roboflow Images	Testing Raw Images
YOLOv5s	Fresh apple:0.98  Rotten apple:0.97 	Fresh apple:0.70  Rotten apple:0.91 
YOLOv8n	Fresh apple:0.98  Rotten apple:0.98 	Fresh apple:0.97  Rotten apple:0.95 

The result plots for the detection of lettuce growth after 100, 200 and 300 training epochs are shown in Fig 7 (a) and (b). Three plots (box, objectness, and classification loss) are used to represent the loss values. The bounding box loss of the fruit detection and classification is shown by the box loss plot, the average detection loss value is shown by the objectness loss plots, and the average classification loss value is shown by the classification loss plot. Therefore, the accuracy for the training dataset on fruit grading increases with decreasing loss values for the box, objectness, and classification loss. Likewise, the test dataset of lettuce growth is referred to by the val box loss plot, val objectness loss plot, and val classification loss plot. In the meanwhile, the test dataset of fruit grading is used for the val box loss plot, val objectness loss plot, and val classification loss plot. On the other hand, plots, recall, and precision are used to gauge performance metrics. Plots show that the YOLOv8 model has the best accuracy, recall, and precision of 99.36%, 97.53%, and 97.85% than YOLOv5. The higher the values, the more accurate the detection and classification of fruit grading. As a result, the YOLOv8 model exhibits excellent performance in identifying and classifying fresh and rotten fruit.



(a)



(b)

Fig 7 *Result for training plots of box loss, objectness loss, classification loss, precision, recall and mAP over the training of 300 epochs for training and validation datasets YOLOv5s (a) YOLOv8n (b)*

4. Conclusion

This project reviews fruit detection and classification in great detail with an emphasis on using deep learning models to improve accuracy. The suggested system sources its images from Google and Kaggle and applies the Roboflow software for annotation and preprocessing. YOLO-based deep neural networks as YOLOv5 and YOLOv8 in particular are used to identify and categorize both fresh and rotten fruit. After testing, YOLOv8 it achieves mAP scores of 99.36% at 242 per 300 epochs that outperforming YOLOv5 and it stopped at 242 epochs as there is no improvement during training process. With its superior performance and reduced computational complexity, YOLOv8 is considered the best model for fruit recognition. Besides that, with an effective and automated method for identifying and grading fruits, the use of YOLOv5 and YOLOv8 in fruit grading represents a substantial advancement in machine learning technology and will increase productivity in the fruit business and agriculture.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The author attests to having sole responsibility for the following: planning and designing the study, data collection, analysis and interpretation of the outcomes, and paper writing.

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