AI-Assisted Grading on *Harumanis* Mango

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Abstract. In recent years, the increasing demand for fruits has presented significant challenges for fruit farmers and distributors, particularly in the realm of effective fruit management. A crucial aspect of this management is fruit grading, which is essential for assessing quality. Traditional manual grading methods, however, are prone to errors and inefficiencies, leading to inaccurate assessments of fruit maturity and quality. These inaccuracies cause substantial economic losses for distributors and hinder farmers' ability to deliver high-quality fruits to the market. This study focuses on the *Harumanis* mango (Mangifera indica Linn), which requires precise grading to meet market standards. By implementing an AI-assisted grading solution, distributors can efficiently grade *Harumanis* mangoes based on weight, size, and surface cleanliness, leading to significant reductions in labor costs and processing time. Our system's precision allows for strategic pricing according to grades, maximizing profitability. Testing of the system demonstrates its feasibility, with the classification model achieving 84% accuracy, the grading model 82% accuracy, and the weight estimation model reaching a low mean square error of 0.00184. These results highlight the potential of our AI-assisted grading solution to replace conventional manual methods, offering consistency and efficiency in fruit grading.

Keywords. AI-assisted grading; *Harumanis* mango; Fruit management; Machine learning; Quality assessment.

1. Introduction

The perishable nature of fruits presents significant challenges in the grading process, particularly in ensuring consistent quality assessments and supply chain efficiency. Traditional manual grading methods, often used in Malaysia's fruit industry, are labor-intensive, time-consuming, and prone to errors, leading to inconsistent quality assessments and reduced efficiency. This inconsistency not only impacts the profitability of farmers but also affects the overall sustainability of the fruit industry, particularly with high-value fruits like the *Harumanis* mango.

The *Harumanis* mango, a prized variety in Malaysia, is graded based on various factors such as size, color, ripeness, and overall quality. However, manual methods struggle to uniformly assess these factors, resulting in grading inaccuracies. These inaccuracies pose significant challenges for farmers and distributors, particularly in meeting the high standards required for exports. The need for a more accurate and efficient grading system is therefore crucial to improving product quality and enhancing the competitiveness of Malaysia's fruit industry in the global market.

This research aims to address these challenges by developing a comprehensive system that utilizes advanced data analytics, including machine learning algorithms and sensor technologies, to accurately grade *Harumanis* mangoes. The proposed system will integrate appearance evaluation, weight estimation, and comprehensive grading models into a cohesive tool that can assess the quality and maturity of mangoes with high precision. By leveraging non-destructive assessment methods, such as advanced image processing algorithms with camera technology, the system aims to improve the efficiency and accuracy of the grading process.

The anticipated outcomes of this research include the development of a user-friendly tool that enables stakeholders to make informed decisions, ensuring that only high-quality fruits reach the market. This tool could significantly enhance the grading process, reduce waste, and promote more resource-efficient agricultural and distribution practices. Moreover, by aligning with broader sustainability goals, the research aims to contribute to reducing the ecological footprint associated with food production and distribution.

Ultimately, this research seeks to bridge the gap between traditional fruit grading practices and the possibilities offered by predictive analytics. By fostering a more efficient and sustainable approach to managing the quality of perishable goods, this research has the potential to transform the agricultural supply chain, particularly for high-value fruits like the *Harumanis* mango.

2. Proposed Design

2.1 Design

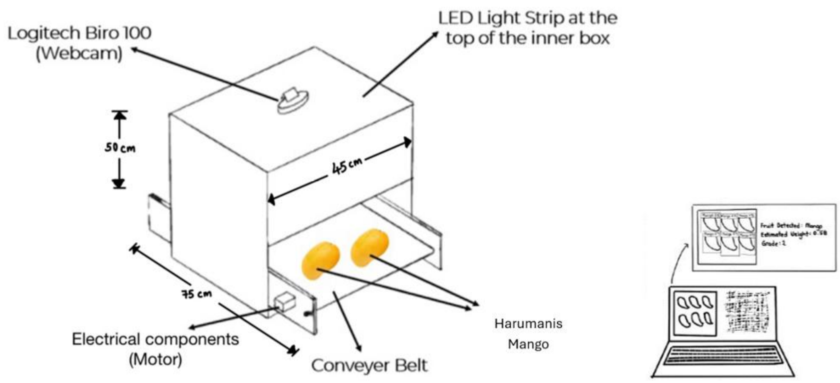

Figure 1: Drawings of our project.

Figure 1 and Figure 2, shows the diagram and the actual developed system which employs a webcam connected to a computer and features an advanced computer vision system. Utilizing a sophisticated deep learning model trained on a comprehensive *Harumanis* mango image dataset, the system accurately detects, grades, and estimates the weight of *Harumanis* mangoes from photos captured by the webcam. The model, fine-tuned with extensive data on various *Harumanis* mango sizes and weights, ensures precise grading and weight estimation exclusively for *Harumanis* mangoes, without detecting other mango varieties. This setup significantly enhances sorting efficiency and supports quality control and streamlined supply chain management in the agricultural sector

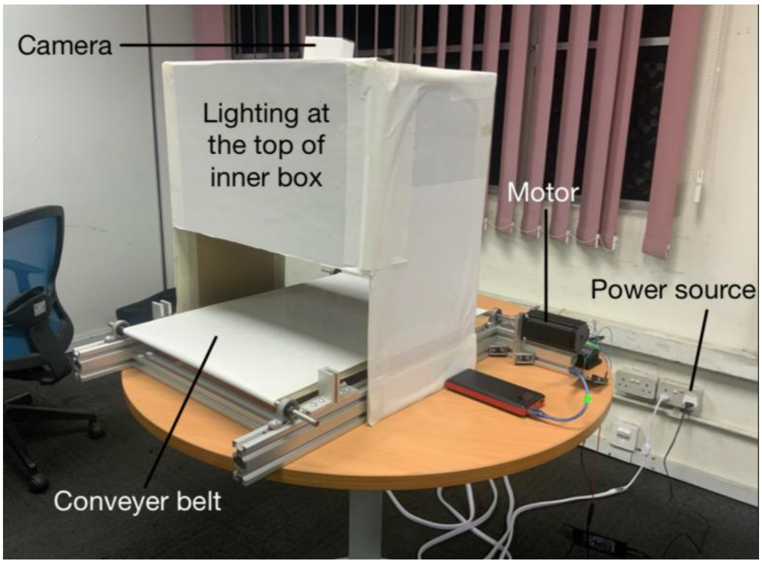

Figure 2: The developed system of our project

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2.2 Technique and Software Used

The first method is using image processing. The developed image processing system for mango analysis is a user-friendly tool that utilizes advanced recognition algorithms to quickly analyse uploaded mango photos. With a meticulously trained deep learning model, the system identifies mango varieties, quality, and potential defects, providing prompt and detailed information within seconds. This seamless integration of image processing and artificial intelligence makes it an invaluable tool for farmers, distributors, and mango enthusiasts, offering precise insights into captured mango images.
The second method is using Yolov8 model. YOLOv8 was chosen for the mango grading system due to its balance of speed and accuracy, essential for real-time processing of large volumes of mango images. Its advanced feature extraction capabilities allow for precise detection of mango attributes, even in high-throughput environments. Additionally, YOLOv8's scalability makes it adaptable to various hardware setups, from powerful GPUs to more constrained devices, ensuring efficient operation across different deployment scenarios. This combination of features makes YOLOv8 a suitable choice for accurately and swiftly grading *Harumanis* mangoes based on visual quality.

2.3 Dataset Preparation

To understand the collection and grading process of the Harunmanis Mangoes, a visit to an orchard managed by Federal Agricultural Marketing Authority (FAMA) in Perlis was made. Figure 3 shows the fruit collected on site.

During the dataset preparation phase, extensive research was conducted to identify a suitable dataset for use in machine learning. However, obtaining *Harumanis* mangoes during this period proved to be both costly and impractical due to the seasonal nature of the fruit, which is typically available from mid-May to early July. As a result, acquiring fresh samples for dataset creation was not feasible. To address this challenge, an alternative approach was pursued, focusing on locating a relevant and available dataset online rather than generating a new one from scratch, which would have been time-consuming.

Figure 3: *Harumanis* Mango collected in Perlis

The search led to the discovery of a dataset on Kaggle named "MangoMassNet-552 Dataset," which contains 548 images of *Harumanis* mangoes. These images were collected from the Fruit Collection Center, FAMA Perlis, Malaysia. The dataset is well-structured, with images resized according to an A4 paper ratio of 8:10. Each mango sample was photographed on top of a blank A4 sheet, which was used as a visual cue for mass estimation.

Despite its usefulness, the dataset presents a significant limitation: it does not include proper annotations or labels for the mangoes. Instead, a separate file is provided, which contains the actual weights and the grading based on FAMA standards, as shown in Figure 4. This necessitates a substantial effort to manually label and annotate each mango into its respective grade categories—namely, Grade P, Grade 1, and Grade 2. Although this process is time-consuming, it is essential for achieving better accuracy and ensuring that the dataset is more controllable and reliable for subsequent machine learning applications.

By undertaking the manual annotation process, the dataset can be tailored to meet specific research requirements, ultimately leading to more precise and meaningful outcomes. This approach, though labor-intensive, is crucial for enhancing the overall quality and accuracy of the machine learning models that will be developed for *Harumanis* mango grading.

Fruit No	Color_K-Yellow_P_Green	Fruit Grade	Mass(kg)
1a.jpg	P	2	0.5
2a.jpg	P	2	0.5
3a.jpg	P	2	0.35
4a.jpg	P	2	0.45
5a.jpg	P	2	0.5
6a.jpg	P	2	0.4
7a.jpg	P	2	0.7
8a.jpg	P	2	0.45

Figure 4: The excel sheets that contain in the dataset obtained

To do the annotation of each mango images, an online tool called CVAT has been discovered. This CVAT tool is a powerful solution for annotating images and videos in computer vision applications. CVAT enable users to label objects with precision, supporting various annotation types such as bounding boxes, polygons, polylines, and key points. These tools allow collaborative annotation workflows, efficient import or export of annotations in multiple formats, and integration with machine learning frameworks for seamless model training. By using this tool, we have successfully annotated each of the images and .txt file which contained the information have been saved. Figure 5 is a screenshot of the manual annotation process using CVAT.

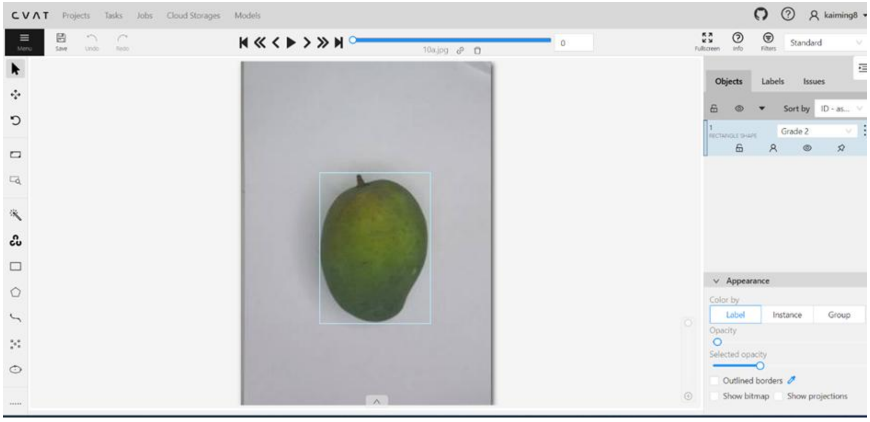

Figure 5: The annotation process of the dataset

Following the annotation process, the dataset was split into three categories: training, testing, and validation. Each category serves a distinct purpose: the training set is used for model training, the validation set for tuning the model parameters, and the test set for evaluating the model's performance on unseen data. To prevent overfitting, disturbance elements were introduced into the dataset, ensuring that the model generalizes well to new data and does not merely memorize the training examples.

In addition to the dataset preparation, a 'data.yaml' file was created, which is essential for initiating the model training process. This file specifies the desired classes and their corresponding names, such as "Grade 1," ensuring that the model accurately recognizes and categorizes the different grades of mangoes during training. This structured approach ensures a robust training process, leading to a model that is both accurate and reliable in grading *Harumanis* mangoes.

2.4 Data processing and training the model

After cleaning and preparing the dataset, the model training process can commence. To achieve this, several key modules were implemented, including Keras, YOLOv8, TensorFlow, cv2, and sklearn. For the classification of mangoes, YOLOv8 was utilized as a pretrained model, with further training conducted to adapt it specifically for mango classification. This additional training was necessary because the COCO class in YOLOv8 does not include mangoes, containing instead over 30 other classes such as "person" and "cat." As a result, custom training was required to effectively recognize mangoes.

During the training process, achieving the desired results proved challenging. Objects with similar size and shape to mangoes were sometimes incorrectly classified as mangoes, a problem often stemming from insufficient training or an uncleaned dataset. This necessitated multiple trials to refine the model and improve accuracy, a time-consuming process with unpredictable outcomes as it was difficult to determine in advance which trial would yield the best results.

Moreover, the innovative approach of estimating mango weights using only a camera posed significant challenges. This method, while promising, is relatively unexplored, with limited research available on the subject. Estimating mango weight from an image is complicated by the presence of surrounding objects or signals that can interfere with the analysis. Additionally, environmental factors can influence results, as the weight estimation relies on a reference object. In the current design, an A4 sheet of paper was used as a reference for weight estimation, as shown in Figure 6 below. The model was trained by feeding it images of *Harumanis* mangoes alongside their actual weights, allowing the system to learn and make accurate predictions.

Figure 6: *Harumanis* Mango on A4 paper

After getting the weights and the colour of the mangoes, the data is being fed into another training to obtain the grades of the fruits. This training of the model used the similar algorithm with the previous model. In short, the picture will be captured by using Logitech Brio 100. The images will be transferred to the computer for cloud computing. Cloud computing is used instead of edge computing as cloud computing can provide better GPU for model training and testing. The captured picture will be passed into the model to the classification of the mango. Then, the weights of the mango will be predicted by using the model. The weights and colour of the mango will be the key for the next step to do grading. Thus, the results will be shown on the interface for users. Figure 7 below shows the flow of the system.

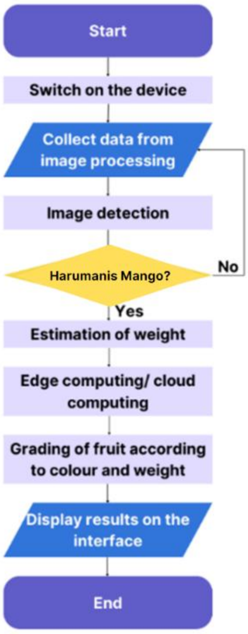

Figure 7: Flowchart of the Project.

3. Implementation and Testing

3.1. Detection of Harumanis Mango

The trained model based on YOLOv8 model demonstrated impressive results in mango detection. The model consistently achieved high precision and recall rates, showcasing its efficacy in accurately identifying mangoes within diverse images. The mAP score further validated the model's reliability and its ability to generalize well to new data.

Figure 8 illustrates that as the number of epochs increases, the class loss steadily decreases. Additionally, the loss continues to decrease until it reaches a certain point, indicating that the model is not overfitting and avoiding false positive results. If the loss decreases too quickly and approaches zero, it suggests that the model is failing to perform its tasks effectively. While the current results may not be optimal, they are acceptable given the constraints of limited budget and resources. However, there is room for improvement in the model's accuracy and a reduction in false positives through expanding the dataset and hyperparameter tuning

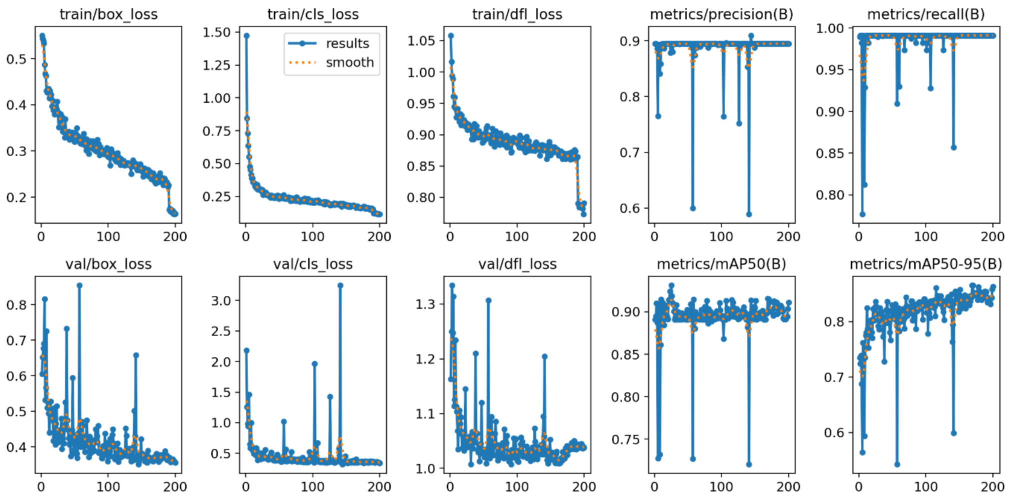

Figure 8: Analysis of the training of the model.

In the testing scenario, mangoes are placed on a conveyor belt, which moves them into the camera's field of view. The camera captures every frame and sends the images to the computer for processing, while the conveyor belt continues moving throughout the process. To evaluate the model for detecting *Harumanis* mangoes, two testing scenarios were set up:

a) *Harumanis* mangoes only: All images consist of *Harumanis* mangoes only
b) *Harumanis* mangoes combined with non-*Harumanis* mangoes

Other types of fruits were excluded from the testing, as the application of the Harumanis mango grading system is unlikely to encounter other fruits in detection scenarios. Due to budget constraints, testing was conducted using six unique Harumanis mangoes purchased from vendors. The model was tested with various combinations of Harumanis mangoes and non-Harumanis mangoes, with each scenario featuring different numbers of both types of mangoes as shown in Figure 9 and Figure 10 below.

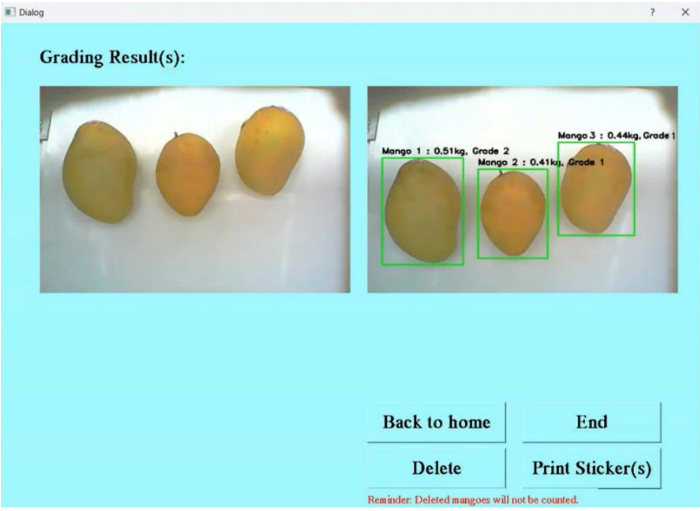

Figure 9: Three Harumanis mangoes successfully detected

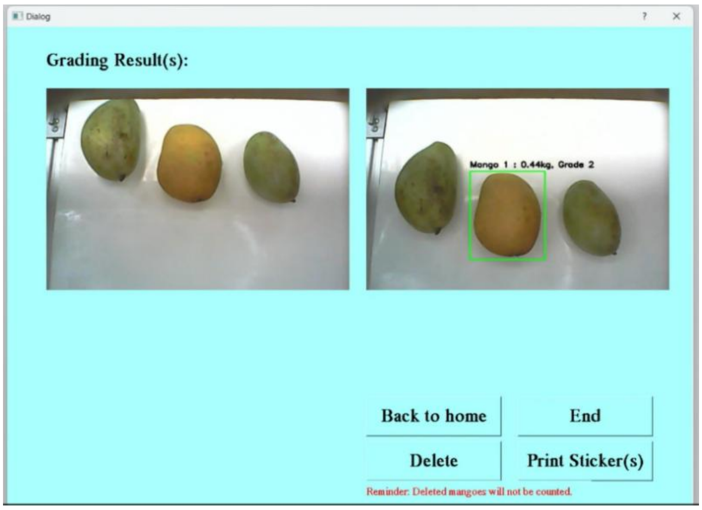

Figure 10: One Harumanis mango successfully detected while mixing with two non-Harumanis mangoes

In the testing process, six *Harumanis* mangoes were purchased, and the testing was conducted by swapping different combinations of these mangoes and mixing them with non-*Harumanis* mangoes. According to the results in Table 1, the detection model achieved an accuracy of 84.38% in identifying *Harumanis* mangoes. The model successfully detected the mangoes even when several passed through simultaneously, demonstrating its efficiency in recognizing *Harumanis* mangoes.

This process serves as a basic but crucial step for distributors, helping to ensure that the mangoes purchased from farmers are genuine *Harumanis* mangoes and not mixed with other varieties to deceive buyers and increase profits. This additional measure acts as a safeguard for distributors, reducing the risk of fraud

Table 1: The accuracy of the detection of the Harumanis Mangoes

	Actual Number of *Harumanis* Mangoes	**Predicted Number of *Harumanis* Mangoes**	**Accuracy (%)**
1	3	2	66.67
2	4	3	75.00
3	3	3	100.00
4	2	2	100.00
5	4	4	100.00
6	4	2	50.00
7	3	3	100.00
8	2	2	100.00
9	3	2	66.67
10	4	3	75.00
Average Accuracy (%)			84.38

3.2. Weight Estimation Model

Estimation of weights of mangoes based on image involved lots of learning to achieve accurate predictions. Estimating the weight of mangoes based on pictures involves regression, where the goal is to predict a continuous value (the weight) from input features (image data). In our studies, Convolutional Neural Networks (CNN) architecture is capable of accurately estimating the mass of mangoes from RGB images.

The images which formed the dataset used in this study were obtained from [4]. There are a total of 548 images in the dataset. In the training of the model, the image is resized to width = 192 and height = 264 and are normalised to make sure all the data have the same sample size. Figure 11 shows the training process of the CNN model with epochs of 250 and batch size 32, and Figure 12 shows the generated plot of the model loss during the training process.

```
Epoch 248/250
10/10 [==============================] - 0s 37ms/step - loss: 0.0135 - mse: 2.9772e-04 - val_loss: 0.0547 - val_mse: 0.00
52
Epoch 249/250
10/10 [==============================] - 0s 38ms/step - loss: 0.0138 - mse: 2.9564e-04 - val_loss: 0.0587 - val_mse: 0.00
59
Epoch 250/250
10/10 [==============================] - 0s 37ms/step - loss: 0.0168 - mse: 4.7179e-04 - val_loss: 0.0556 - val_mse: 0.00
51
```

Figure 11: The training of the model with epochs = 250 and batch size = 32

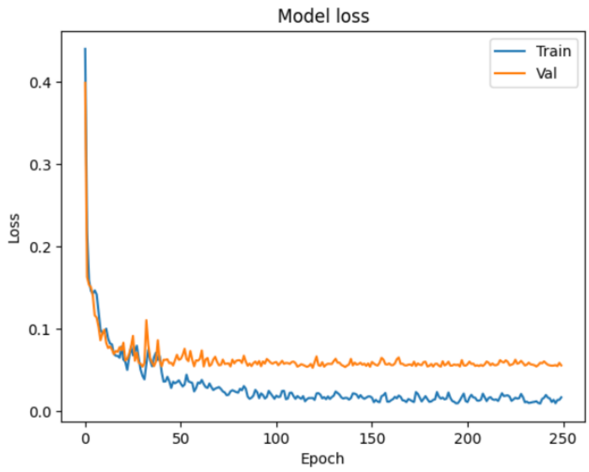

Figure 12: The loss graph throughout the training of the model

```
           no  weight
512  241b.jpg    0.40
93    94a.jpg    0.57
362   89b.jpg    0.58
20    21a.jpg    0.40
86    87a.jpg    0.45
134  135a.jpg    0.60
384  111b.jpg    0.54
54    55a.jpg    0.30
360   87b.jpg    0.45
308   35b.jpg    0.30
1/1 [==============================] - 0s 118ms/step
           no  weight  weight (pred)
512  241b.jpg    0.40       0.426283
93    94a.jpg    0.57       0.610258
362   89b.jpg    0.58       0.583888
20    21a.jpg    0.40       0.403394
86    87a.jpg    0.45       0.453790
134  135a.jpg    0.60       0.574010
384  111b.jpg    0.54       0.543128
54    55a.jpg    0.30       0.305307
360   87b.jpg    0.45       0.461480
308   35b.jpg    0.30       0.305606
```

Figure 13: The comparison of actual and prediction results after training of the model.

In the *Harumanis* mango grading system, mean squared error (MSE) is utilized as a metric to evaluate the model's accuracy. This method involves comparing the predicted weights of the mangoes, as determined by the model, with their actual weights measured using a calibrated weight balance. This comparison assesses the closeness of the model's predictions to the true values, providing a quantitative measure of its performance.

Before testing, each *Harumanis* mango is carefully weighed using a calibrated weight balance, establishing the ground truth data that serves as a benchmark for evaluating the model's accuracy. The actual weight of each mango is recorded to create a dataset of true values for comparison. Figure 13 shows the comparison of actual and prediction results obtained.

During testing, *Harumanis* mangoes are placed on the conveyor belt for weight estimation. Each mango is weighed five times, and the average results are recorded in Table 2 below. The differences between the real weights and the estimated weights are recorded and converted to percentages for evaluation.

Table 2: The tabulation of actual and estimated weights of Harumanis mangoes.

No	Grade	Actual Weight (kg)	Estimated Weight (kg)	Difference of weight (%)	(Actual – Estimated)^2
1	P	0.4494	0.45	–0.1335	3.60×10^{-7}
2	P	0.5582	0.47	15.8008	7.78×10^{-3}
3	1	0.4298	0.42	2.2801	9.60×10^{-5}
4	1	0.4232	0.42	0.7561	1.02×10^{-5}
5	2	0.3828	0.38	0.7315	2.80×10^{-3}
6	2	0.3314	0.35	–5.6126	3.46×10^{-4}
Average of difference (%)				**4.2191**	
Mean Squared Error				**0.00184**	

From Table 2, it is evident that, on average, the difference between the estimated weight and the actual weight measured by a weighing balance is as low as 4.22%, amounting to only a few grams of difference. This indicates that the model is relatively accurate, achieving a 95.78% accuracy in estimating the weights of *Harumanis* mangoes using only the captured images for this estimation. Additionally, the mean squared error (MSE) in testing is notably low, at just 0.00184.

An MSE of 0.00184 suggests that the average squared difference between the predicted and actual mango weights is minimal. This high precision indicates that the model performs exceptionally well in predicting weights with very few errors. Such a low MSE reflects a well-trained model that can be reliably used for grading *Harumanis* mangoes based on weight. This allows distributors to process and sort mangoes more quickly and efficiently than manual sorting, with less physical contact from workers, as they no longer need to weigh the mangoes individually before placing them into baskets.

3.3. Grading model

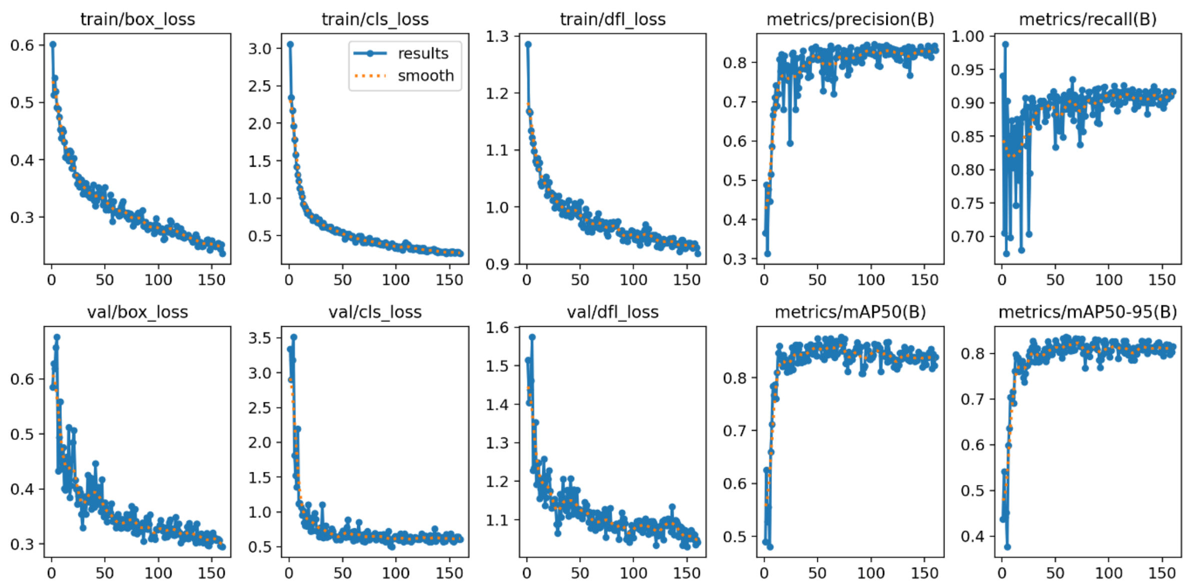

Figure 14: The information on the grading model

```
285 epochs completed in 0.430 hours.
Optimizer stripped from runs/train/exp5/weights/last.pt, 14.3MB
Optimizer stripped from runs/train/exp5/weights/best.pt, 14.3MB

Validating runs/train/exp5/weights/best.pt...
Fusing layers...
Model summary: 157 layers, 7018216 parameters, 0 gradients, 15.8 GFLOPs
                 Class     Images  Instances          P          R      mAP50
                   all         71         59      0.763      0.939      0.876      0.849
               Grade 1         71         25      0.855          1      0.887      0.864
               Grade 2         71         12      0.743          1      0.913      0.913
               Grade P         71         22      0.691      0.818      0.828      0.771
Results saved to runs/train/exp5
```

Figure 15: The training of the model using YoloV5

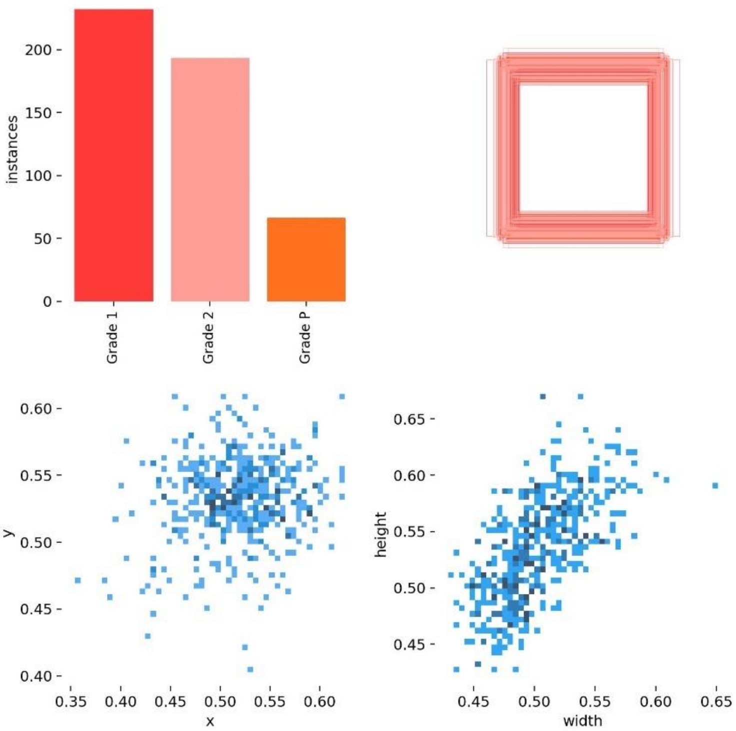

Figure 16: Information during the training progress.

During the testing phase, Yolov8 consistently outperformed Yolov5 in both speed and accuracy. Yolov8's advanced architecture and optimized operations enabled it to deliver faster inference times and higher precision in detecting objects. While Yolov5 also performed well, it did not achieve the same levels of efficiency and accuracy as Yolov8.

When comparing Yolov8 to Faster-RCNN, it was observed that Faster-RCNN achieved slightly higher accuracy in object detection. However, this improvement came at the cost of significantly increased detection time, with Faster-RCNN requiring approximately 3-4 seconds per detection. This delay poses a significant drawback in large-scale industrial environments, where rapid processing and minimal latency are essential. The cumulative effect of such delays can lead to substantial performance bottlenecks, making Faster-RCNN less viable despite its accuracy. Consequently, the decision to base the grading model on Yolov8 was driven by the need for both speed and accuracy. While Faster-RCNN and Yolov5 either did not yield satisfactory results or required excessive time for detection, Yolov8 provided an optimal solution. Yolov8's balanced performance ensures it can handle high-throughput requirements without compromising the quality of detections. Figure 14 shows the training results of the grading model and Figure 15 shows the training of the model using YoloV5.

However, Figure 16 reveals a significantly higher number of Grade 1 and Grade 2 *Harumanis* mangoes compared to Grade P *Harumanis* mangoes. This imbalance in the dataset results in a high DFL loss during training. DFL, a specialized loss function for object detection, typically declines as the model optimizes. However, due to the unequal distribution in the dataset, the DFL loss cannot be reduced to a very low value.

During the testing of the grading model, mangoes are placed onto the conveyor belt one by one. The grades of the *Harumanis* mangoes detected by the system are recorded in a table and compared with the grades provided by the distributor. The following Table 3 display the three different grades of *Harumanis* mangoes: P, 1, and 2.

Table 3: Actual and predicted grades of the Harumanis mangoes used for testing.

No	Actual Grade	Predicted Grade
1	P	1
2	P	1
3	1	1
4	1	1
5	2	2
6	2	2

The grading results displayed in the interface indicate that both Grade 1 and Grade 2 mangoes were predicted accurately using the grading model. However, Grade P mangoes were categorized as Grade 1, which can be attributed to the poor appearance of these mangoes. According to the FAMA standard, Grade P mangoes should weigh approximately 600g with a 10% tolerance and exhibit minimal dark or brown spots on their skin. As seen in the figures above, the dark or brown spots on the mangoes classified as Grade P are extensive, although their weights fall within the acceptable range for this grade.

The dataset obtained online, along with images captured during a visit to Perlis, show that both Grade P Harumanis mangoes typically have exceptionally good surface quality, as depicted in the comparison images below. The Grade P mangoes received for testing were found to have blemished surfaces, which would classify them as Grade 1 based on visual inspection.

The blemished condition of the Grade P mangoes could be due to their delivery process and the timing, as it was near the end of the Harumanis mango season. Harumanis mangoes are highly susceptible to environmental changes, which can cause their appearance to deteriorate before reaching their destination. Additionally, the fact that the mangoes were obtained at the end of the season may have contributed to their suboptimal condition compared to mangoes harvested during peak season. For comparison, the following figures depict the mangoes purchased for testing and the Grade P mangoes photographed during a visit to the facility in Perlis in early April. It is evident that the mangoes from the earlier visit displayed little to no surface imperfections.

4. Conclusion

In conclusion, the proposed system combines a computer vision system with a deep learning model trained on a comprehensive dataset of *Harumanis* mango images. By analyzing only the mango pictures, the system can accurately identify the *Harumanis* mango species and then grade them based on weight, size, and surface cleanliness. This approach reduces the need for additional components, simplifying the setup to just a camera.

Moreover, our system adheres to industrial standards by incorporating a conveyor system, which streamlines the grading process and ensures consistency and efficiency in handling large quantities of mangoes. However, for demonstration purposes, the conveyor system can handle only a limited number of *Harumanis* mangoes at a time.

With the implementation of this solution at the beginning of the fruit supply chain, fruit farmers and distributors will benefit the most as they can better grade and label their inventory before distribution to wholesalers. They can strategically price their fruits based on their condition, leading to increased profitability. Additionally, improved labelling enhances the buying experience for consumers, enabling them to make informed decisions when purchasing their favourite fruits.

This solution holds significant potential for revolutionizing fruit management, offering a more efficient and sustainable approach that can enhance current grading systems. By eliminating extra components while maintaining high accuracy, the system promises substantial improvements over existing market solutions. Implementing such systems could lead to positive changes, including better resource utilization, reduced waste, and improved overall sustainability in the agricultural sector.

Acknowledgements

The author acknowledges the Federal Agricultural Marketing Authority (FAMA) and Associate Professor Dr. Fathinul Syahir Ahmad Saad of Universiti Malaysia Perlis (UNIMAP) for providing the *Harumanis* images and expertise. To Ms. Siti Nasrin binti Mohd Asri, a seller at Pusat Jualan *Harumanis*, for her practical knowledge and contributions during our interview sessions.

References

[1] Department of Standards Malaysia (2012). *Fresh mangoes - Specification MS 885:2012*.

[2] F. S. A. Sa'ad, M. F. Ibrahim, A. Y. M. Shakaff, A. Zakaria, and M. Z. Abdullah, "Shape and weight grading of mangoes using visible imaging," *Computers and Electronics in Agriculture*, vol. 115, pp. 51-56, 2015/07/01/ 2015, doi: https://doi.org/10.1016/j.compag.2015.05.006.

[3] M. F. Ibrahim, F. S. Ahmad Sa'ad, A. Zakaria, and A. Y. Md Shakaff, "In-Line Sorting of *Harumanis* Mango Based on External Quality Using Visible Imaging," *Sensors*, vol. 16, no. 11, p. 1753, 2016. [Online]. Available: https://www.mdpi.com/1424-8220/16/11/1753.

[4] M. H. B. Ismail, M. N. Wagimin, and T. R. Razak, "Estimating Mango Mass from RGB Image with Convolutional Neural Network," in *2022 3rd International Conference on Artificial Intelligence and Data Sciences (AiDAS)*, 7-8 Sept. 2022 2022, pp. 105-110, doi: 10.1109/AiDAS56890.2022.9918807.

[5] M. H.Ismail and M. N.Wagimin. *MangoMassNet-552 Dataset*, Kaggle, doi: 10.34740/KAGGLE/DSV/3987156.

[6] M. Mavi, Z. Husin, R. B. Ahmad, Y. Mohd Yacob, R. Farook, and W. Tan, "Mango ripeness classification system using hybrid technique," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 14, pp. 859-868, 05/01 2019, doi: 10.11591/ijeecs.v14.i2.pp859-868.

[7] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 18-23 June 2018 2018, pp. 4510-4520, doi: 10.1109/CVPR.2018.00474.

[8] W. Aung, T. T. Thu, H. T. D. Aye, P. P. Htun, and N. Z. Aung, "Weight Estimation of Mango from Single Visible Fruit Surface using Computer Vision," in *2020 59th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE)*, 23-26 Sept. 2020 2020, pp. 366-371, doi: 10.23919/SICE48898.2020.9240422.

[9] W. Spreer and J. Müller, "Estimating the mass of mango fruit (Mangifera indica, cv. Chok Anan) from its geometric dimensions by optical measurement," *Computers and Electronics in Agriculture,* vol. 75, no. 1, pp. 125-131, 2011/01/01/ 2011, doi: https://doi.org/10.1016/j.compag.2010.10.007. (Ismail, 2022)

[10] Mohammad Hafiz bin Ismail, & Mohd Nazuan Wagimin. (2022). MangoMassNet-552 Dataset [Data set]. Kaggle. https://doi.org/10.34740/KAGGLE/DSV/3987156