Real-time object detection to classify export quality of mangosteen using variants of you only look once version 8

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ABSTRACT

Mangosteen is one of the leading export commodities from Indonesia. Despite its great economic potential, only about 25% of Indonesian mangosteens meet export standards, mainly due to visual defects such as yellow sap and spots on the skin of the fruit. The process of sorting export-worthy mangosteens has been done manually, which tends to be time-consuming and inconsistent. Therefore, this study aims to utilize artificial intelligence technology in building a real-time image recognition model to improve the efficiency and accuracy of the export-quality mangosteen sorting process. This study uses you only look once version 8 (YOLOv8) as an image recognition model with YOLOv8 variants, including nano, small, medium, large, and extra large variants. The results of the study using 4,014 primary and 255 secondary data of mangosteen, the highest performance is reached by YOLOv8 medium 82% of accuracy, 0.856 of mean average precision (mAP)50, and 0.616 of mAP50-95. This result is obtained from 70% training, 20% validation, and 10% testing data with epoch stop 85. These results indicate that the model can provide good performance in mangosteen export quality classification. This research contributes to the fields of agricultural technology and artificial intelligence by offering an innovative solution to a practical problem, enhancing efficiency, accuracy, and scalability in export-quality mangosteen sorting.

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1. INTRODUCTION

Mangosteen fruit, known as the queen of tropical fruit, is one of the fruits widely cultivated in the agricultural sector. As one of the most important export commodities in Indonesia, mangosteen generates income for the country and farmers [1]–[3]. However, one of the main problems in the mangosteen production system is low quality due to yellow sap disease and fruit skin spots that are still not included as quality fruit for export. Because of the demands of the international market share for high-quality and safe-to-consume products, producers must be able to produce high-quality mangosteen fruit [4]–[7]. The main factor causing low mangosteen exports is its low quality. Only 25% of Indonesian mangosteen fruit meets export standards. Export-worthy quality is determined by the level of smoothness of the fruit (skin and yellow sap on the fruit) and the size of the fruit. Yellow sap contaminates the flesh and skin of the fruit.

Because it stains the skin of the fruit, it causes the skin of the fruit to become dull and unattractive, and causes a bitter taste.

The primary challenge in the mangosteen export chain is a lack of transparency in quality standards by farmers. Mangosteen fruit is worthy of export is a fruit that passes several stages of farmer sorting, warehouse sorting, and exporter sorting. The sorting process has been done manually by looking at the surface of the fruit and the fruit stalk. Sorting that is done manually focuses on the size, diameter, color, stalk, texture, and pattern of the fruit. The surface of the fruit that does not have white spots (snow disease), yellow spots (yellow sap), or even cracking is one of the reasons for quality fruit. In addition to the surface of the fruit, the stalk is also one of the benchmarks for the quality of the fruit. Of course, this sorting process takes longer because it has to be checked one by one on the fruit and is done by farmers. The rapid development of artificial intelligence technology for image recognition can be used to help farmers in the process of sorting mangosteen fruit automatically. The image recognition model can certainly be embedded in various devices that help the sorting process more efficiently. Image recognition is a technology used in various industries such as health, security, sales, and technology to recognize objects, people, writing, and actions in digital images [8]. Previous research has proven the role of artificial intelligence in image recognition in various fields, such as healthcare applications for medical image analysis that improve the speed and accuracy of interpreting medical images, aiding in diagnostics and treatment planning [9]. A decision support system that provides comprehensive information to healthcare professionals, enhancing decision-making capabilities [9]. Then, in intelligent driving systems (autonomous vehicles), image recognition enables vehicles to understand their surroundings in real-time, which is crucial for safety and automation in intelligent driving systems. In the security sectors, facial recognition and object detection can ensure and enhance monitoring and safety [9]. In retail, image recognition streamlines inventory management and enhances customer experience by accurately identifying products, even with subtle packaging differences [10].

In agriculture, image recognition has emerged as a breakthrough technique that improves crop management and disease detection. Farmers may use advanced algorithms to identify plant illnesses, classify soil types, and monitor insect infestations, thereby increasing agricultural output and sustainability. Various image processing techniques, including convolutional neural networks (CNNs) and support vector machines (SVMs), have shown high accuracy in identifying crop diseases [11]–[14]. Image recognition tools can classify soil types and recommend suitable crops, cultivations, and fertilizers based on parameters like soil color and location [15]. Then, hybrid models combining logistic regression with decision trees have also been effective in improving recognition accuracy [12]. In other research, automated systems utilizing image recognition can diagnose pests and diseases, facilitating precision monitoring and reducing pesticide usage [16]. Deep learning algorithms, such as you only look once (YOLO), have been applied to various agricultural scenarios, demonstrating their versatility and effectiveness [17].

YOLO has a performance that is worth considering for object detection. YOLO is outperform comparing with single shot detection (SSD) and faster region-based convolutional neural networks (Faster R-CNN) in an identical testing environment [18]. Other applied studies report YOLOv8 yields higher inference speed and competitive or superior mean average precision (mAP) compared with SSD, Faster R-CNN, and efficient object detection (EfficientDet) in traffic and surveillance tasks [19], [20]. Its optimization allows for deployment in agricultural systems, enabling real-time grading and sorting without high-end hardware. Therefore, YOLOv8 can offer the optimal speed, detection accuracy, and deployability for practical applications such as mangosteen quality inspection. One of the image recognition methods that shows good results from various studies is deep learning, which accelerates the learning process in neural networks with many layers of computation. One of the many deep learning algorithms is the CNN algorithm on the YOLO architecture [21]. YOLO's architecture enables it to forecast bounding boxes and class probabilities straight from photos, making it ideal for a variety of applications such as service robots, remote sensing, and live object recognition. Variants such as YOLOv4, YOLOv5, and YOLOv8 have been tuned for performance, with YOLOv8 demonstrating significant increases in detection precision, particularly for small targets [22]. Based on YOLOv8's anchor-free design, updated backbone or neck, modern loss and training scheme produce improved mAP and inference efficiency versus many earlier YOLO releases (such as YOLOv5), and studies specifically report YOLOv8 outperforming YOLOv5 in traffic sign and general detection tests [23]–[25].

Among the uses of deep learning in agricultural image recognition research, there is limited research that has focused on applying advanced object detection models to mangosteen export quality. Existing studies have mostly used traditional image processing or classical machine learning methods. By applying YOLOv8 to this novel agricultural context, this research not only contributes to advancing precision agriculture in Indonesia but also provides a transferable model for other export commodities with similar grading challenges. Therefore, this study aims to assist sorting in the mangosteen industry by using one of the deep learning methods, namely image recognition using YOLOv8, as well as to determine the performance of the model built with various YOLOv8 variants.

2. METHOD
2.1. Research activity
This research adapts the cross-industry standard process for data mining (CRISP-DM) methodology, which is widely used in data mining and machine learning projects. This methodology has six main stages, namely business understanding, data understanding, data preparation, modeling, evaluation, and deployment. Figure 1 shows research activities that adapt the stages of CRISP-DM. At the business understanding stage, it was found that the process of sorting export-quality mangosteens took quite a long time due to the limited number of farmers. Therefore, by utilizing artificial intelligence technology, the process of sorting export-worthy mangosteens can be more efficient with image recognition techniques. Furthermore, at the data understanding stage, this study requires information on the characteristics of export-worthy mangosteens and collects mangosteen data from mangosteen plantations and sorting places for export. The data needed are images of mangosteens individually or many mangosteens in one image. In addition, this study also uses video data to test the real-time detection model.

Furthermore, for the modeling process, 15 experiment scenarios were designed based on a combination of three data splitting ratios for training, validation, and testing, namely 80:10:10, 70:20:10, and 60:20:20, with a combination of 5 available YOLOv8 architecture variants, namely nano, small, medium, large, and extra large. Then, the evaluation was conducted using a confusion matrix. Lastly, a simple deployment process is carried out by implementing the best model from the model development results into the mangosteen detection application. The results of the deep learning model for sorting the export eligibility of mangosteen using YOLOv8 have great potential to be implemented in the future. This model can be applied to better technology-based systems, such as web applications, mobile devices, or internet of thing (IoT)-based automated systems to assist the fruit sorting process in real time. By integrating the model into the production system, farmers and exporters can increase the efficiency and accuracy of the sorting process, thereby increasing the chances of Indonesian mangosteens meeting export standards.

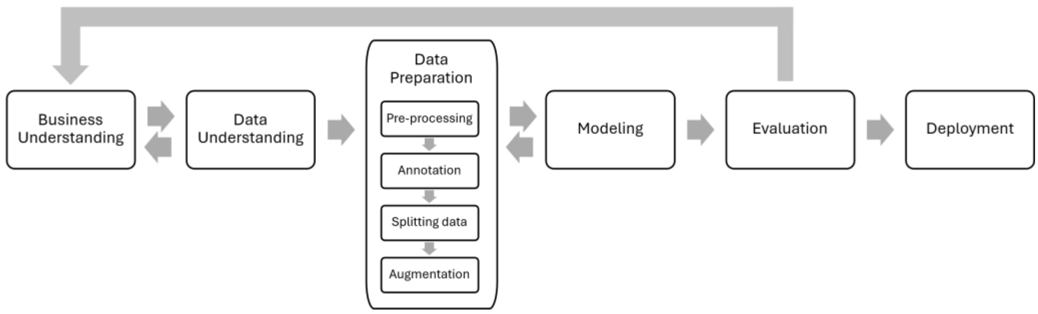

Figure 1. CRIPS-DM adoption for research activities

2.2. Mangosteen datasets
Export-worthy mangosteen fruit can be identified from the surface or skin of the fruit, color, stalk, and disease. The surface will greatly affect the standard of eligibility of mangosteen fruit, as well as the color to measure the ripeness of the mangosteen fruit. Then, the quality of the stalk will always affect the quality of the mangosteen fruit [26]. In addition, mangosteen fruit that has a disease (there are sap or yellow spots on the surface) is categorized as mangosteen that is not worthy of export.

This study has two types of data, divided into primary and secondary data. Data in the form of mangosteen fruit images, either one mangosteen or many mangosteens. Figure 2 shows an example of a mangosteen image used in this study. Primary data was collected from mangosteen plantations and sorting locations in the Mataram area, West Nusa Tenggara, one of Indonesia's largest mangosteen producers and sorting centers. Primary data was collected on December 18, 2023, December 6, 2024, and December 18, 2024, using the iPhone XR, iPhone XS Max, Redmi Note 12 Pro, and Samsung A35 devices. This device certainly affects the lighting and image quality.

The secondary dataset was obtained from the internet with existing search engines, such as Google and Kaggle at https://www.kaggle.com/datasets/mariameres/deep-learning-klasifikasi-jenis-buah-manggis, to increase data variation and be able to recognize various conditions or appearances of mangosteen, such as lighting variations, shooting angles, and image quality, using mangosteen images taken from various sources on the internet. The combination of these two datasets was carried out to enrich the model in recognizing and classifying mangosteen fruit correctly in various conditions. The mangosteen image data that was successfully collected in this study were 2,717 primary data (https://s.id/mangosteen_dataset), and 1,297 secondary data.

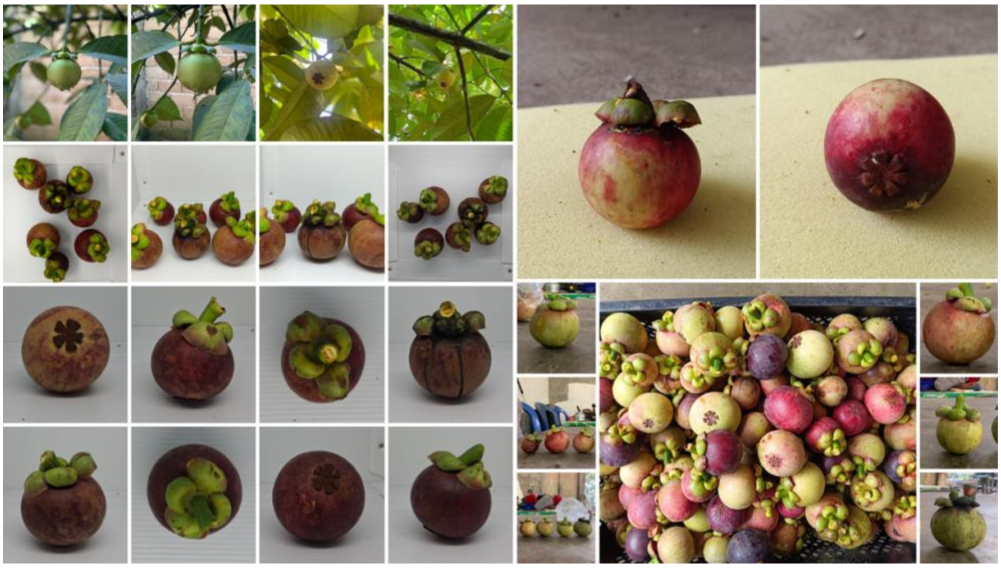

Figure 2. The primary mangosteen datasets from plantation field

2.3. You only look once version 8

Image identification utilizing the YOLO algorithm has gained popularity due to its efficiency and accuracy in real-time item detection. YOLO's architecture enables it to forecast bounding boxes and class probabilities straight from photos, making it ideal for a variety of applications such as service robots, remote sensing, and live object recognition. YOLO thrives in real-time applications, with high accuracy rates and low latency, which is essential for activities that require quick feedback. Variants such as YOLOv4, YOLOv5, and YOLOv8 have been tuned for performance, with YOLOv8 demonstrating significant increases in detection precision, particularly for small targets [22]. YOLO improves visual identification capacities in complex situations [27] and under different conditions [28]. Despite its benefits, YOLO struggles with small object detection and multi-object settings. To solve these difficulties, innovations like modified loss functions and multi-scale training have been developed [28]. The use of advanced approaches, such as normalized Wasserstein distance loss, has increased detection accuracy in specialized applications [22].

YOLO uses the CNN method, which is widely applied to image data, a method for detecting objects. YOLO processes images in real-time at forty-five (45) frames per second [29]–[32]. The YOLO architecture as shown in Figure 3, including the YOLOv8 version, consists of three main components: backbone, neck, and head, which work synergistically to detect and classify objects. In YOLOv8, the backbone uses the cross-stage partial darknet (CSP Darknet) architecture designed to efficiently capture patterns and visual characteristics of images. CSP Darknet utilizes residual connections to improve feature learning without losing information during data propagation. Through several layers of convolution and activation functions, the backbone produces a rich feature representation, which is then forwarded to the next section. The neck is a component that connects the backbone to the head and is responsible for combining features from various scales (multiscale feature aggregation). In YOLOv8, the neck uses the path aggregation network (PANet) mechanism, which improves the fusion of features from deeper and shallower layers. PANet helps the model understand the context of objects of different sizes, thus increasing the accuracy in detecting small and large objects. Meanwhile, the head is the last part of the YOLO architecture that is responsible for making predictions, namely determining the presence of objects, object types, and the position (bounding box) of the object in the image. YOLOv8 uses a decoupled head that separates the tasks of object location regression (bounding box regression) and object label classification. Table 1 shows the characteristics of each YOLOv8 variation that will be used in this study [33].

Table 1. Characteristics of YOLOv8

Variant	Model size	Number of parameters (million)	Speed
YOLOv8n (nano)	Very small	3.2	Very fast
YOLOv8s (small)	Small	7.2	Fast
YOLOv8m (medium)	Medium	21.2	Medium
YOLOv8l (large)	Large	46.5	Slow
YOLOv8x (extra large)	Very large	87.7	Very slow

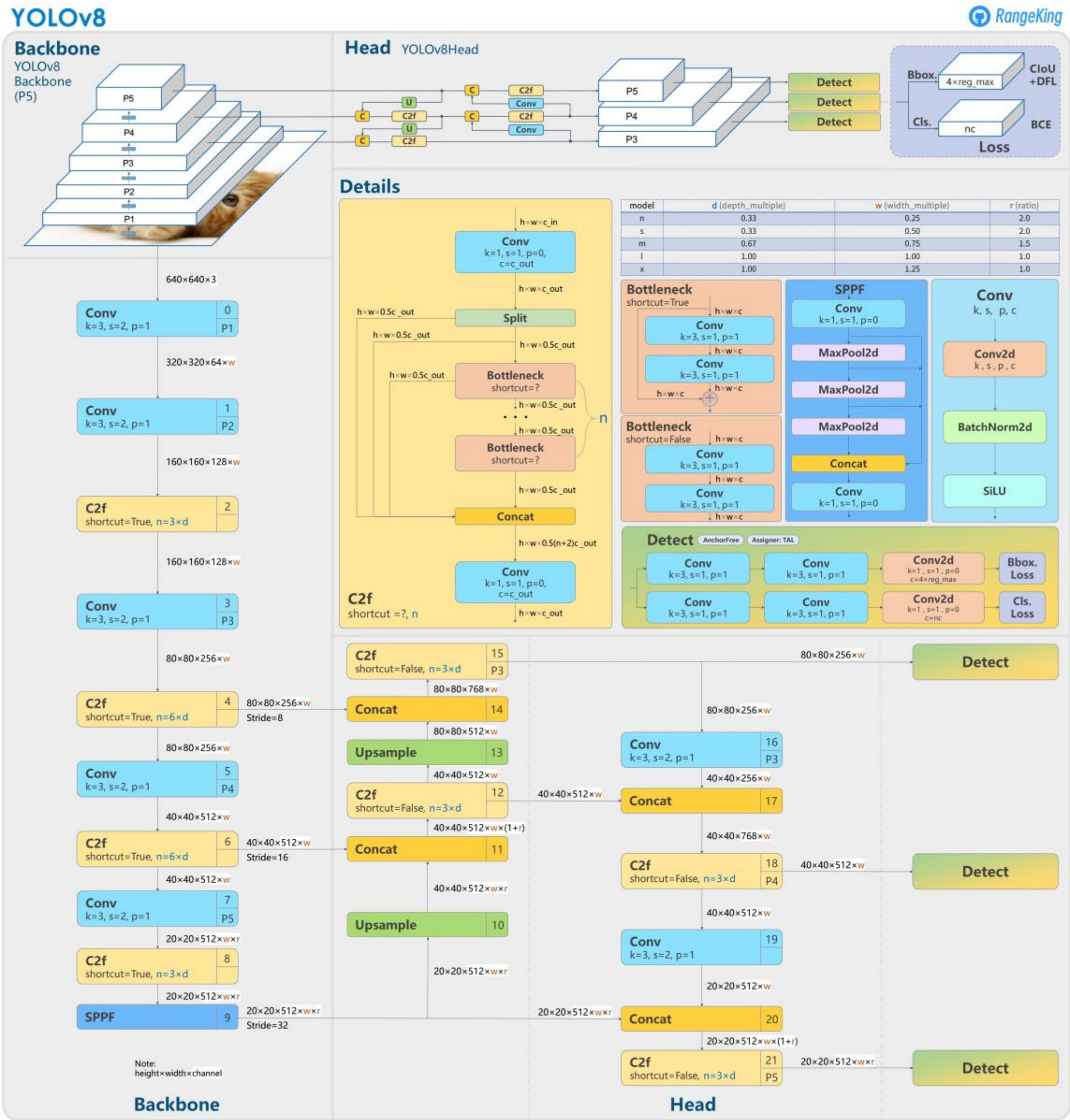

Figure 3. YOLOv8 architecture [34]

3. RESULTS AND DISCUSSION

This section presents the research results, starting with data preparation. It then covers the modeling, evaluation, and deployment phases. Finally, a comprehensive discussion is provided at the end of the section.

3.1. Data preparation

There are 4 stages of data preparation in this study, including data pre-processing, annotation, splitting, and data augmentation. Based on the understanding of the data that has been collected, the image extensions vary from JPG, JPEG, and PNG, so all are standardized into JPG. Then the various sizes of the images range from kilobytes to megabytes, with an average size of 2.6 megabytes (3,024 px×4,032 px) for the primary dataset and 500 kilobytes (718 px×420 px) for the secondary dataset, so that all image sizes are standardized to 608 px×608 px. The annotation process is then carried out using Roboflow to mark the mangosteen fruit in the image. This annotation stage labels the mangosteen fruit into two categories, namely export-worthy and unworthy. The results of the mangosteen annotation were obtained with a total of 4,014 mangosteen fruits, with a distribution of 2,717 fruits from primary data and 1,297 from secondary data. Table 2 shows the distribution of feasible and unfit labels after carrying out the annotation process on the annotated mangosteen fruit image.

Table 2. Distribution of mangosteen annotation

Data sources	Number of export worthy	Number of export unworthy	Total annotation
Primary	1,602	1,115	2,717
Secondary	856	441	1,297

Then, the data splitting and augmentation process is carried out sequentially. After the process of dividing the training, validation, and testing data with a ratio variation of 80:10:10, 70:20:10, and 60:20:20, the next step is the data augmentation process, with the augmentation results, as shown in Table 3. This augmentation process aims to enrich the dataset because the deep learning method on YOLOv8 is more optimal for large data [35]–[39]. Some of the augmentation mechanisms used include rotating, cropping (0-15%), and bounding box flip.

Table 3. Distribution of splitting and augmentation data

Splitting ratio	Activity	Primary (augmentation) data	Secondary (augmentation) data	Total (augmentation) data
80:10:10	Training	1,379 (4,137)	196 (588)	1,575 (4,725)
	Validation	172	24	196
	Testing	171	24	195
70:20:10	Training	1,209 (4,137)	172 (513)	1,380 (4,650)
	Validation	342	48	391
	Testing	171	24	195
60:20:20	Training	1,038 (3,546)	148 (444)	1,186 (3,990)
	Validation	342	48	390
	Testing	342	48	390

3.2. Modeling and evaluation result

The model-building experiment in this study combines five YOLOv8 variants, namely nano, small, medium, large, and extra large, with variations in splitting data training, validation, and testing. The results of the experiment were then evaluated using a confusion matrix that shows the values of accuracy, precision, and recall using (1) to (3) [40]. The experiment was carried out using a hyperparameter configuration in the form of a maximum epoch of 100, a batch size of 16, and a patience of 20. The use of a uniform hyperparameter configuration ensures that the difference in performance between scenarios comes entirely from the data ratio and model architecture variants, without being influenced by differences in training parameters. The results of this stage are in the form of precision, recall, and accuracy. These values will be the benchmark for the success of the model for this study, and the accuracy results are given a threshold confidence value of 0.5 and 0.7.

$$Accuracy = \frac{TP+TN}{Total\ Data\ Test} \quad (1)$$

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

These three equations have a crucial role in evaluating the performance of the object detection model used in the study [41], [42]. Accuracy measures the overall correctness of the model's predictions on the test dataset. Precision evaluates the reliability of positive predictions, and recall measures the model's ability to find all relevant positive cases. Besides, this model is also evaluated using mAP50 and mAP50-95. The metrics mAP50 and mAP50-95 are critical for assessing the performance of object identification algorithms, providing information about their accuracy and robustness. mAP50 calculates the mAP at an intersection over union (IoU) criterion of 0.50, whereas mAP50-95 averages the average precision across several IoU thresholds ranging from 0.50 to 0.95. This dual technique enables a full assessment of model performance [43]–[45]. Figure 4 shows an example of the YOLOv8 training process to recognize mangosteens that are suitable and unsuitable for export. Where a value of 1 indicates a mangosteen that is suitable for export, while a value of 0 indicates a mangosteen that is unsuitable for export. Furthermore, Figure 5 shows an example of the validation labels and prediction process for mangosteens, "*layak*" means "worthy", while "*tidak layak*" means "unworthy". Last, the model testing stage is illustrated in Figure 6.

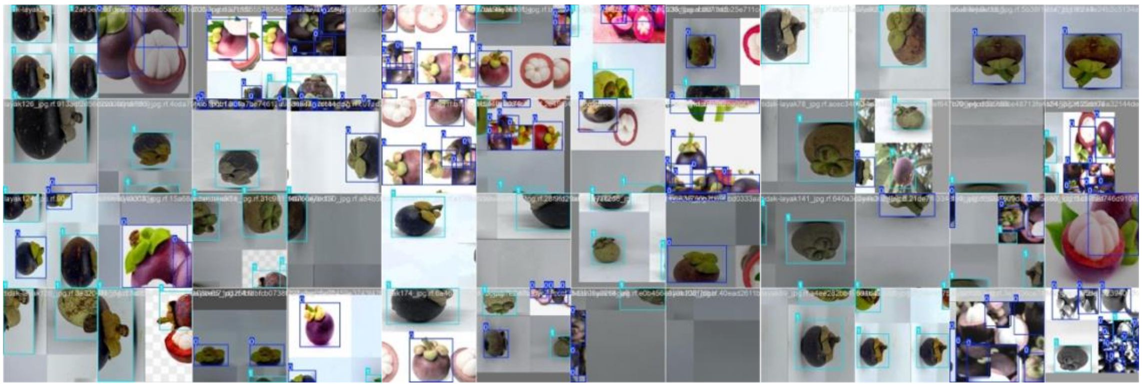

Figure 4. The example of the training process with primary and secondary mangosteen datasets

Figure 5. The example of the validation process with primary and secondary mangosteen datasets

Figure 6. The example of testing process with primary and secondary mangosteen datasets

Based on the results of experiments with 15 YOLOv8 variant scenarios as in Table 4, it shows that the nano variant has the best accuracy results in detecting the export eligibility of mangosteen fruit. However, high accuracy is not the only determining factor in the quality of the YOLOv8 variant, because other factors affect the quality of the variant, including datasets and other hyperparameters. The results of each model that has been built greatly affect the quality of the model, dataset, and several other parameters. The experimental results show evidence that only the two best scenarios exceed the expected accuracy limit of 70%, almost all the 80:10:10 and 70:20:10 splitting scenarios with the YOLOv8 achieving accuracy values more than 70%, except YOLOv8 nano with splitting data 80:10:10. The highest values are highlighted in blue color in the Table 4.

Table 4. Experiment result

Spliting	YOLOv8 variants	Stopped epoch	Precision	Recall	Accuracy (%)			mAP50	mAP50-95
					Training	Testing			
						Conf. 0.5	Conf. 0.7		
08:10:10	Nano	75	0.817	0.668	**83**	40	69	0.767	0.507
	Small	85	0.832	0.697	80	50	71	0.777	0.521
	Medium	73	0.823	0.689	81	47	70	0.776	0.525
	Large	75	0.871	0.655	81	45	70	0.782	0.534
	Extra large	81	0.827	0.694	80	50	72	0.782	0.529
70:20:10	Nano	97	0.907	0.792	71	69	81	0.848	0.603
	Small	84	0.898	0.77	68	60	78	0.842	0.601
	Medium	85	0.905	**0.813**	72	**70**	**82**	0.832	0.602
	Large	98	**0.911**	0.75	65	58	76	**0.856**	**0.616**
	Extra large	100	0.909	0.79	67	65	80	0.848	0.603
60:20:20	Nano	85	0.576	0.682	51	33	45	0.647	0.321
	Small	78	0.598	0.67	48	31	45	0.663	0.324
	Medium	89	0.598	0.663	51	35	48	0.652	0.322
	Large	46	0.511	0.75	50	22	45	0.637	0.321
	Extra large	83	0.598	0.66	49	50	51	0.657	0.322

The experimental results in Table 4 show that the YOLOv8 medium variant model with 70:20:10 data splitting has the best performance with the highest recall value, which is 0.813. The highest accuracy value is 73% for a confident score of 0.5 and 82% for a confident score of 0.7. The highest precision, mAP50, mAP50-95, is reached by the YOLOv8 large variant with 70:20:10 data splitting in sequence 0.911, 0.856, and 0.616 compared to other models. However, the YOLOv8 nano variant has a fairly high epoch stopping time, which stops at epoch 80 when the model has converged (stable). This YOLOv8 nano variant also has the best accuracy value for a confidence value of 0.5 for all data splitting variations. Data splitting 80:10:10 has the best training process accuracy value, which is 83% in the nano variant.

This study found alignment with previous studies where the YOLOv8 nano variant had the highest accuracy in recognizing objects [46]. The YOLOv8 medium variant had the highest precision value in detecting objects [47]. Higher YOLOv8 variants certainly require expensive computing resources. Conversely, smaller models like YOLOv8 nano provide a practical solution for real-time tasks with limited resources [47], [48]. While larger datasets generally increase image processing quality, attention should also be paid to data representativeness and quality. Balancing size and quality are critical for achieving optimal model performance. Increasing the number of training data improves classifier performance, as seen in land cover mapping experiments where accuracy peaked at a specified training/test ratio [49].

Larger datasets are extremely beneficial in neural networks, such as deep learning, which consider each sample during training. They help determine class borders more accurately. However, while high-quality training data is required for best model performance, the trade-offs between data quality and quantity must also be considered. High within-image diversity, which includes a variety of objects, and low compression artifacts in datasets, improves the performance of image super-resolution models [50]. Effective preprocessing procedures, including resizing, normalization, data augmentation, and cropping, are critical for improving data quality [51].

Besides mangosteen, the proposed YOLOv8-based framework can be generalized to other high-value tropical export commodities such as durian, avocado, and dragon fruit, which also require precise grading based on surface texture, color uniformity, and physical defects. Actually, several studies have also conducted fruit post-harvest quality control using YOLO, such as kiwifruit [52] and apple [53]. The adaptability of the model architecture and data pipeline enables transfer learning, where pretrained weights from mangosteen datasets can be fine-tuned for new fruit types with minimal additional data collection. This scalability opens opportunities for developing an integrated, artificial intelligence-driven postharvest inspection system that supports Indonesia's broader agricultural export sector, enhancing competitiveness and consistency in global markets.

3.3. Deployment

The deployment process is built simply using frameworks such as PyTorch with GPU support and TensorFlow to run the YOLOv8 model. The inference engine used is OpenCV to process images in real-time. Adequate RAM is essential. Therefore, previous research recommends using devices that typically require at least 4 GB to handle the model's operations efficiently [54]. In addition, Flask is used to build an inference application programming interface (API) if the model is accessed via a network service. The best model from the experiment is selected in the deployment process. Figure 7 shows an example of the best model deployment in detecting mangosteens that are worthy and unworthy for export, making it easy and efficient in the sorting process. This model can detect 85% correctly of mangosteen in real-time.

Figure 7. The example of real-time mangosteen detection with secondary and primary video

4. CONCLUSION

This work successfully created a real-time mangosteen sorting model that uses the YOLOv8 algorithm to categorize export-quality fruit based on visual characteristics such as skin flaws and stalk condition. The experimental results show that the YOLOv8 medium variation performed best overall, with the highest accuracy 82%, but the YOLOv8 nano variation provided a realistic solution for real-time tasks, maintaining stable performance at a lower computing cost, where it achieved the highest training accuracy (83%). The proposed model offers a dependable and effective technique for grading mangosteen quality, improving compliance with stringent export regulations, and increasing Indonesia's agricultural competitiveness in international markets. Therefore, this study confirms prior findings on the efficiency of smaller models like YOLOv8 nano for resource-limited environments and the importance of larger models like YOLOv8 medium and large for high-precision tasks. It also emphasizes that dataset size and quality are critical factors in optimizing deep learning model performance. Increasing data diversity, improving preprocessing steps, and balancing data quality with quantity are essential to enhancing model accuracy and generalizability. Future research could increase the dataset's diversity to increase the model's generalizability across different environmental circumstances and mangosteen kinds. Furthermore, new optimization approaches like hyperparameter tuning and quantization may improve the accuracy and deployment efficiency of higher YOLOv8 variations. Integrating the model with automated sorting hardware, such as conveyor belts or robotic arms, and testing its performance in real-world scenarios will help to prove its scalability and feasibility. Extending this method to other export commodities may widen artificial intelligence's impact in improving agricultural systems.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The authors state that the research is related to regulations and institutional policies.

DATA AVAILABILITY

The availability of the primary and secondary data, including:

– Primary data was collected from mangosteen plantations and sorting locations in the Mataram.
– Secondary data was collected from the internet with existing search engines, such as Google and Kaggle at https://www.kaggle.com/datasets/mariameres/deep-learning-klasifikasi-jenis-buah-manggis.

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