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Optimization of Palm Fruit Ripeness Detection With Yolov11 on CPU

Abstrak

Industri kelapa sawit merupakan salah satu sektor strategis yang berkontribusi besar terhadap perekonomian Indonesia. Namun demikian, industri ini masih menghadapi berbagai tantangan, terutama pada aspek efisiensi operasional dan penerapan digitalisasi, khususnya di tingkat petani swadaya yang seringkali masih menggunakan metode manual dalam menentukan tingkat kematangan buah. Proses manual tersebut rentan terhadap subjektivitas, sehingga dapat berdampak pada kualitas panen dan efisiensi rantai pasok. Dalam menjawab permasalahan tersebut, penelitian ini mengusulkan sistem deteksi kematangan buah kelapa sawit berbasis algoritma YOLOv11, pemilihan ini karena keunggulannya dalam kecepatan inferensi serta akurasi deteksi, khususnya ketika dijalankan pada perangkat dengan sumber daya terbatas. Model yang dikembangkan kemudian diimplementasi menggunakan Framework ONNX Runtime. Dengan hal tersebut memungkinkan percepatan proses inferensi mendukung portabilitas pada perangkat keras dengan sumber daya terbatas. Hasil Pengujian menunjukan bahwa model mencapai tingkat akurasi mAP@50 sebesar 90.2% dengan latensi rata-rata sekitar 255 ms hingga 300 ms. Dengan capaian tersebut, sistem ini tidak hanya andal dalam mendeteksi kematangan buah, tetapi juga efisien dalam waktu pemrosesan serta relevan untuk mendukung transformasi digital di sektor perkebunan sawit..

Kata kunci*—Deteksi Objek, Kematangan Buah Kelapa Sawit Mentah, Yolov11, ONNX Runtime, Unit Pemroses Pusat.*

Abstract

The palm oil industry is one of the strategic sectors that contributes significantly to the Indonesian economy. However, this industry still faces various challenges, particularly in terms of operational efficiency and the implementation of digitalization, especially at the level of independent farmers who often still use manual methods to determine the ripeness of the fruit. This manual process is prone to subjectivity, which can impact harvest quality and supply chain efficiency. To address this issue, this study proposes a palm oil fruit ripeness detection system based on the YOLOv11 algorithm, chosen for its advantages in inference speed and detection accuracy, especially when run on devices with limited resources. The developed model was then implemented using the ONNX Runtime Framework. This enables accelerated inference processes and supports portability on hardware with limited resources. Test results show that the model achieves an mAP@50 accuracy of 90.2% with an average latency of around 255 ms to 300 ms. With these achievements, this system is not only reliable in detecting fruit ripeness, but also efficient in processing time and relevant to support digital transformation in the palm oil plantation sector.

Keywords—*Object Detection, Ripness Crude Oil Palm Fruit, Yolov11, ONNX Runtime, Central Processor Unit.*

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1. INTRODUCTION

Palm oil is one of Indonesia's strategic plantation commodities, playing an important role as a producer of vegetable oil [1]. Based on an article quoted from Gulti Oktariani, the growth of the palm oil industry in Indonesia in 2024 shows an absorption of labor in the agriculture, forestry, and fisheries sectors of 28.64% [2]. However, operational processes in the field, particularly in determining the maturity level of palm fruit, still face significant obstacles. To date, most farmers and field workers still rely on manual methods for sorting fruit, which is highly dependent on individual visual perception.

Amidst the demands of the digital age and global competition, the palm oil industry at the independent farmer level still faces major challenges [3]. Low digital literacy, limited access to information, and a shortage of extension workers in the field have led to gaps in the implementation of sustainable cultivation technologies [4]. If not addressed immediately, this has the potential to reduce the competitiveness of farmers and hinder the sustainability of the industry [5]. In addition, external challenges such as extreme climate change, commodity price fluctuations, and demands for operational efficiency further exacerbate the pressure on this sector [6][7]. In the field, most plantations still use conventional methods with unsystematic manual recording, which hinders the decision-making process and reduces accountability [8].

This study offers a solution through the application of palm fruit detection technology based on the YOLOv11 algorithm. The selection of this algorithm is based on its advantages in terms of detection speed and accuracy, which are obtained through the refinement of anchor-based detection and computational efficiency in image processing. This makes YOLOv11 lighter than its predecessor [9]. Based on the article by Wang, C. Y., et al., YOLOv11 not only presents a more efficient detection algorithm development, but is also relevant for application on servers and devices with limited resources [10]. Thus, this research is the first step in the data-based digital transformation of palm oil plantations, which has the potential to increase operational cost efficiency, especially in limited infrastructure. Previous studies have demonstrated the effectiveness of the YOLO algorithm in agriculture and object detection. Suharjito et al. [11] studied the detection of oil palm ripeness using YOLOv4 with several variants and selected YOLOv4-416 as the best model because it achieved a mAP@0.50 of 99.93% at a speed of 50.9 FPS. The model was then optimized through quantization to remain efficient on mobile devices. Patricia and Benafo [12] compared YOLOv5 and YOLOv7 in food detection cases. The results showed that YOLOv5 excelled in mAP@50, but YOLOv7 was chosen for implementation because it had more consistent precision, recall, and F1-Score. Meanwhile, Sharma et al. [13] compared YOLOv8–YOLOv11 with Faster R-CNN in seed detection. The results show that YOLO algorithms are generally capable of achieving accuracy above 90%, with YOLOv9 recording the highest accuracy of 93.5% and YOLOv11 being the fastest model with an inference time of 8.2 ms and an accuracy of 92.1%. Based on this review, it can be concluded that the YOLO algorithm has great potential in supporting fast and accurate object detection systems in agriculture. However, there has been no specific research implementing YOLOv11 for real-time detection of palm oil fruit ripeness on devices with limited resources. Therefore, this study focuses on the application of ONNX Runtime based YOLOv11, which can be run efficiently on CPU devices, thereby supporting the digital transformation of oil palm plantations towards smart agriculture.

2. METHODS

This research method was designed systematically with the main objective of developing a computer vision-based oil palm fruit ripeness detection system, as shown in Figure 1. The research process began with the collection of data in the form of images of oil palm fruits from various field conditions, followed by a manual annotation process to label them according to their ripeness category (unripe, underripe, ripe, and overripe). Once the data is ready for use, the next step is to set the hyperparameters, which include determining the batch size, learning rate, number of epochs, and other parameters relevant to model training. The model training stage is carried out using the selected deep learning architecture, then the model results are analyzed through performance evaluation to identify the potential for overfitting or underfitting based on specific evaluation metrics such as accuracy, precision, recall, and mAP. If the evaluation results show that the model's performance meets the specified criteria, the model will be exported into ONNX file format so that it can be integrated into the implementation stage in mobile applications or decision support systems in the field.

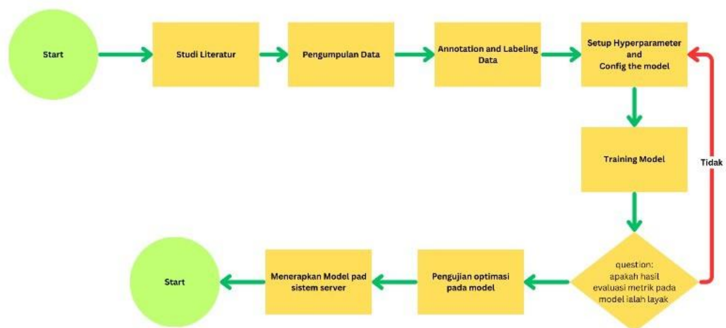

Figure 1. Model Development Flow

Based on this flowchart,the stages of this research can be explained in more detail as follows:

2.1 Data Collection

At this stage, data collection used previous research data entitled “An Ordinal Dataset for Ripeness Level Classification in Oil Palm Fruit Quality Grading” taken from the Mendeley dataset repository platform. To add image data, this study took sources from the Roboflow platform, collecting a total of 5778 images. In this study, there are 6 labels for ripeness levels, namely unripe, semi-ripe, ripe, overripe, empty, and abnormal.


Figure 2. Image data based on oil palm maturity level

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2.2 Data Annotation

Data annotation is a crucial stage in object detection research, especially when done manually. This process aims to label each object in an image according to a predetermined class. The level of accuracy and consistency of annotation greatly affects the quality of training data, because deep learning models can only achieve optimal performance if the images and labels used are completely accurate. As shown by Bilal et al. (2024), differences in the quality of annotations produced by annotators with varying levels of expertise have been shown to result in significant variations in model performance, making clear annotation standards and the involvement of experts important factors in ensuring model reliability [14]. This is also in line with the findings of Paullada et al. [15] and Peng et al. [16], which emphasize the importance of annotation quality in supporting the success of object detection models.

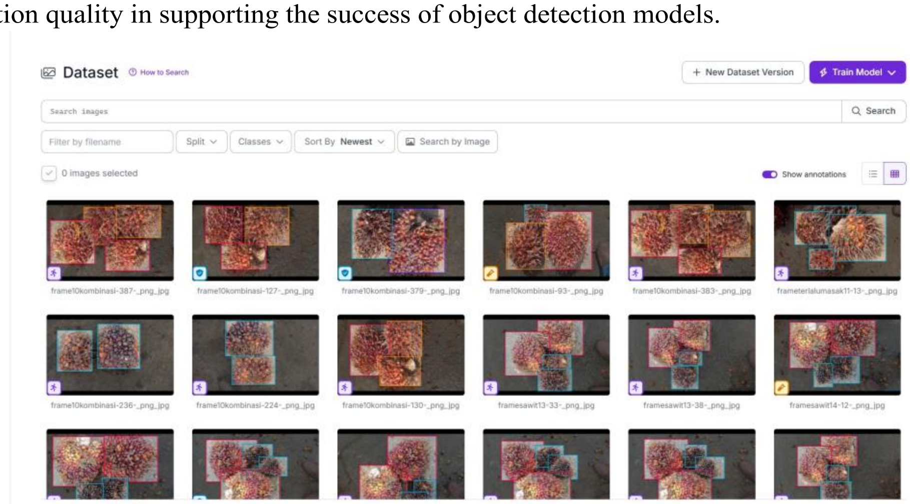

Figure 3. Dataset After Annotation

In this study, each oil palm fruit object in the image was carefully annotated using the Roboflow platform so that the model could understand the visuals of each category . Accuracy at this stage is crucial, because even small errors in labeling can impact the model's performance, both in terms of accuracy and generalization ability. Therefore, the annotation process is carried out with clear standards so that the object detection results obtained are optimal. Figure 3 shows an example of a dataset that has been marked with a bounding box according to its class.

2.3 Setup Data Augmentation and Hyperparameter

In this study, each oil palm fruit object in the image was carefully annotated using the Roboflow platform so that the model could understand the visuals of each category . Accuracy at this stage is crucial, because even small errors in labeling can impact the model's performance, both in terms of accuracy and generalization ability. Therefore, the annotation process is carried out with clear standards so that the object detection results obtained are optimal [17]. Figure 3 shows an example of a dataset that has been marked with a bounding box according to its class.

Parameter	Deskripsi	Nilai
Imgsz	Ukuran gambar dilakukan pada training model	640
Epochs	Jumlah iterasi penuh pada seluruh dataset	20
Batch Size	Jumlah sampel yang diproses dalam satu kali iterasi	8
Learning rate initial	Laju pembelajaran awal untuk mengatur kecepatan konvergensi model	0.001
Optimizer	Algoritma optimisasi yang digunakan	Auto
Weigh decay	Regulasi untuk mencegah *overfitting*	0.0005
Box	Bobot fungsi kerugian untuk prediksi bounding box	7.5
Cls	Bobot fungsi kerugian untuk klasifikasi objek	0.85
Dfl	Bobot fungsi kerugian *Distribution Focal Loss*	1.0
Hsv_h	Augmentasi citra berdasarkan perubahan hue	0.0015
Hsv_s	Augmentasi citra berdasarkan perubahan saturasi	0.5
Hsv_v	Augmentasi citra berdasarkan perubahan value (kecerahan)	0.4
fliplr	Probabilitas *flip horizontal* (membalik gambar secara horizontal)	0.5
flipud	Probabilitas *flip vertical* (membalik gambar secara vertikal)	0.1
scale	Faktor skala untuk augmentasi ukuran citra	0.3
translate	Faktor translasi untuk pergeseran citra	0.05
Mixup	Teknik augmentasi dengan menggabungkan dua gambar	0.1
Mosaic	Teknik augmentasi dengan menggabungkan empat gambar menjadi satu	1.0
patience	Jumlah *epoch* tanpa peningkatan sebelum *early stopping* dijalankan	10

In this study, hyperparameter settings were adjusted gradually through a process of experimentation to find the most optimal combination. For example, learning rate adjustments were used to control the speed at which the model learned patterns, while the number of epochs and batch size were adjusted to make the training process more stable and prevent overfitting. With the right hyperparameter settings, it is hoped that the model can achieve a balance between high accuracy and good generalization capabilities [18].

In addition, this study also uses a data augmentation process applied to Yolo simultaneously with data augmentation model training with the aim of expanding the variety of the dataset so that the model developed in this study is able to learn from more diverse image conditions, such as changes in color, lighting, rotation, and image combination techniques [19].

2.4 Evaluation Model

The evaluation stage in this study is designed to assess the overall performance of the developed model, particularly in its ability to generalize to new and unseen test data. This step is crucial because it provides insights into how reliable the system is when applied outside the training environment. To achieve this, several evaluation metrics are employed, each offering a different perspective on the model's detection and classification capabilities [20].

The first metric used is Mean Average Precision (mAP), which is widely recognized as the standard measurement in object detection tasks. This metric evaluates the accuracy of the model in recognizing and localizing objects within images or videos. By comparing predicted results against the actual ground truth, mAP provides a comprehensive measure of how well the model performs in terms of both recognition and localization [21].

In addition to mAP, precision is also considered as an important indicator of performance. Precision measures how accurately the system predicts positive results. In practical terms, a higher precision indicates that the model is capable of producing correct detections with minimal errors, meaning fewer false positives are generated during the detection process [22].

Another key metric is recall, which focuses on the ability of the model to identify all relevant objects present in the dataset. This metric is important because it reflects the system's effectiveness in minimizing missed detections. A higher recall suggests that the model successfully detects a greater portion of object s that should have been identified, ensuring more complete coverage in the detection process [23].

Lastly, the F1-score is introduced as a balanced measure that combines both precision and recall into a single metric. This value is particularly useful in scenarios where there is a need to balance accuracy and completeness. A high F1-score implies that the model not only performs accurately in its detections but also consistently identifies the majority of relevant objects, providing a more holistic evaluation of the system's performance [24].

2.5 Latency Model

Latency or inference delay time is the time interval required from when input data is received by the deep learning model until the output or prediction is generated [25]. In the context of artificial intelligence-based systems, latency is an important indicator because it affects the response speed of the system. The higher the latency value, the longer it takes to receive the output, which can reduce the performance of real-time applications [26]. In this test, we looked at CPU usage percentage, memory usage, and latency.

3. RESULTS AND DISCUSSION

In this study, a palm oil fruit ripeness detection model was developed using Yolov11s. The discussion focussed on two main aspects, namely the evaluation of object detection performance based on accuracy metrics (precision, recall, and mAP) and the evaluation of model inference speed on limited hardware. All testing was conducted using an Nvidia GeForce RTX 4050 Laptop GPU as the model training medium. Meanwhile, model inference testing was run on a device with an AMD Ryzen 7 7735HS processor and 20 GB of RAM.

3.1 Latency Model

The evaluation results show that the Yolov11 model performs very well in detecting and classifying the maturity level of palm fruit. In the evaluation stage using test data, the model achieved an accuracy of 90.2%, while in the validation data, the accuracy obtained was 85.5%. This difference of around 5% shows that the model experienced an improvement in performance on the test data, which indicates fairly good generalization ability. The test results using the training data are shown in Table 2, while the test results using the test data are shown in Table 3.

Class	Images	Instance	Box(P)	R	m@AP50	m@AP50-90
All	555	811	0.815	0.786	0.855	0.584
Matang	165	189	0.858	0.670	0.873	0.639
Abnormal	57	81	0.646	0.778	0.733	0.465
Kosong	69	69	0.916	0.883	0.948	0.659
Mentah	151	195	0.919	0.836	0.895	0.561
Setegah_matang	155	175	0.784	0.731	0.811	0.588
Terlalu_matang	69	85	0.768	0.820	0.874	0.594

Tabel 2. Training Session

Class	Images	Instance	Box(P)	R	m@AP50	m@AP50-90
All	277	385	0.845	0.805	0.902	0.608
Matang	71	78	0.783	0.785	0.865	0.622
Abnormal	23	34	0.765	0.765	0.871	0.488
Kosong	30	38	0.886	0.886	0.956	0.659
Mentah	75	98	0.816	0.816	0.937	0.596
Setegah_matang	86	94	0.691	0.691	0.83	0.629
Terlalu_matang	36	43	0.884	0.884	0.954	0.654

Tabel 3. Testing Session

Based on Table 2 and Table 3, it can be seen that the Ripe and Overripe classes have relatively high detection performance with mAP50 values above 0.87. This indicates that the model more easily recognizes the visual characteristics of these two classes. Meanwhile, the Abnormal and Empty classes tend to have lower mAP values, around 0.73–0.77, which indicates that there are still challenges in detecting palm fruits in these conditions.

3.2 Evaluation Inference Of Object Detetion With Basis Yolov11

The evaluation results show that the YOLOv11 model performs very well in detecting and classifying the ripeness level of palm fruits. In this study, the inference process was run using ONNX runtime on the developed object detection model, with settings specified in Table 4. The following is the SessionOptions configuration in the ONNX Runtime environment.

Nama Konfigurasi	Nilai
intra_op_num_threads	1
allow_spinning	0

Tabel 4. Konfugrasi pada onnx runtime

Based on the evaluation results, the model achieved an accuracy rate of 90.2% on the test set and 85.5% on the validation set. This difference of around 5% shows that the model is able to maintain consistent performance while also having good generalization capabilities for new data. In addition to accuracy, this study also evaluated the efficiency of the inference process to determine the extent to which the optimization configuration affects the use of computational resources. The test results are shown in Table 5.

Mode	Jumlah gambar	*Cpu Utilazation*	*Memory Usage*	*Latency (ms)*
Optimasi	1	6.24%	369.50 MB	230.54
	10	6.23%	509.07 MB	235.75
	17	6.30%	509.70 MB	227.65
Tidak optimasi	1	6.66%	506.80 MB	1604.45
	10	6.63%	512.84 MB	1815.46
	17	6.65%	509.71 MB	1757.52

Table 5. Results of optimization and non-optimization inference using CPU

The evaluation results show that the Yolov11 model performs very well in detecting and classifying the maturity level of palm fruit. In the evaluation stage using test data, the model achieved an accuracy of 90.2%, while in the validation data, the accuracy obtained was 85.5%. This difference of around 5% shows that the model experienced an improvement in performance on the test data, which indicates fairly good generalization ability. The test results using the training data are shown in Table 2, while the test results using the test data are shown in Table 3

In terms of CPU usage, both modes show relatively similar utilization percentages, around 6–7%, so optimization does not add a significant load on the processor. However, the difference is seen in memory consumption. The optimized mode requires between 369 MB and 509 MB of memory, while the non-optimized mode ranges from 506 MB to 513 MB. This shows that in addition to speeding up inference time, optimization can also help reduce memory usage on hardware.

Overall, these results prove that applying optimization to the model not only significantly increases inference speed, but also makes the system more efficient in utilizing computational resources, making it more suitable for implementation on devices with hardware limitations.

4. CONCLUSIONS

This study proves that the ONNX Runtime-based YOLOv11 model is capable of detecting and classifying the ripeness level of palm fruits with high accuracy, namely mAP@50 of 90.2% on test data and 85.5% on validation data, which demonstrates good generalization capabilities. The implementation of the SessionOptions configuration with *intra_op_num_*threads=1 and *allow_spinning* = 0 settings has been proven to significantly improve inference efficiency, with latency almost ten times faster than the mode without optimization, as well as relatively stable CPU usage even though the number of images tested has increased. These results confirm that the developed oil palm fruit ripeness detection system is not only reliable in terms of accuracy, but also efficient in resource usage, making it relevant for real-time implementation on devices with computational limitations.

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