ABSTRAK

EVALUASI ALGORITMA *CNN* DAN *FASTER R-CNN* UNTUK KLASIFIKASI OTOMATIS TINGKAT KEMATANGAN TANDAN BUAH SEGAR KELAPA SAWIT

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Derajat kematangan tandan buah segar (TBS) kelapa sawit menentukan tingkat rendemen, kadar asam lemak bebas, dan stabilitas mutu minyak. Ketidaktepatan panen dapat memicu kerugian nilai di sepanjang rantai pasok. Penilaian manual terhadap tandan sawit yang akan dipanen bersifat subjektif dan tidak konsisten karena dipengaruhi variasi pencahayaan, oklusi pelepah, jarak pengambilan, serta heterogenitas varietas. Otomasi berbasis *computer vision* diperlukan agar keputusan panen terstandar dan dapat diskalakan. Studi ini membandingkan tiga pendekatan *deep learning* untuk klasifikasi kematangan TBS yaitu CNN standar, CNN ber-backbone ResNet50, dan Faster R-CNN ResNet50. Tiga himpunan data digunakan: dataset citra TBS dari perkebunan, 8.400 citra TBS beranotasi rapi dari Roboflow, dan subset Roboflow 625 citra. Evaluasi mencakup akurasi, precision, recall, F1-score, mean Average Precision (mAP), dan kecepatan inferensi (FPS), sehingga trade-off presisi-kinerja dapat dinilai. Hasil pemodelan menegaskan adanya perbedaan kinerja lintas domain. Pada dataset citra lapangan, CNN standar memiliki keunggulan pada penerapan *edge* berdaya terbatas dengan nilai akurasi 83,87%, mAP 84,29%, dan 464 FPS. Spesifikasi ini cukup untuk klasifikasi tunggal *near real-time*. Pada Roboflow 8.400 citra, Faster R-CNN ResNet50 menghasilkan akurasi 92,72%, precision 100%, recall 91,73%, F1 95,63%, mAP 86,25%, dengan 396 FPS, dimana kinerja tinggi ini didorong anotasi bersih dan distribusi visual lebih terkontrol, meski biaya komputasinya lebih besar karena proses deteksi dua tahap dan penggunaan *Region Proposal Network* (RPN). Pada subset Roboflow 625 citra, model Faster R-CNN ResNet50 tetap terbaik (akurasi 92,42%, mAP 81,00%, 307 FPS). CNN ResNet50 konsisten berada di antara keduanya, merefleksikan kapasitas fitur yang lebih kuat dari CNN standar namun tanpa mekanisme proposal wilayah. Secara praktis, CNN standar cocok untuk inspeksi *on-device* berbiaya rendah. Sedangkan Faster R-CNN tepat untuk deteksi multiobjek pada data terstruktur. Pemilihan model sebaiknya mempertimbangkan karakteristik domain, target latensi, serta ketersediaan komputasi.

Kata kunci: Kelapa Sawit, Klasifikasi , *CNN*, *ResNet50*, *Faster R-CNN*, *Deep Learning*.

ABSTRACT

EVALUATION OF CNN AND FASTER R-CNN ALGORITHMS FOR AUTOMATIC CLASSIFICATION OF OIL PALM FRESH FRUIT BUNCH (FFB) RIPENESS LEVELS

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Fresh fruit bunch (FFB) ripeness governs oil yield, free-fatty-acid formation, and product stability; misgrading at harvest propagates losses along the supply chain. Manual grading is subjective and inconsistent under varying illumination, frond occlusion, camera distance, and cultivar heterogeneity. Scalable, computer-vision automation is therefore needed to standardize harvest decisions. This study compares three deep-learning approaches for FFB ripeness classification: standard CNN, CNN with ResNet50 backbone, and Faster R-CNN ResNet50. Three datasets are used: on-farm field dataset imagery, a curated Roboflow set of 8,400 annotated images, and a Roboflow subset of 625 images. The models are evaluated in term of accuracy, precision, recall, F1-score, mean Average Precision (mAP), and inference speed (FPS) to quantify precision–throughput trade-offs. Results confirm domain-dependent performance. On field imagery, the standard CNN is preferable for resource-constrained edge deployment with 83.87% accuracy, 84.29% mAP, and 464 FPS. It is sufficient for single-object, near-real-time classification. In addition to Roboflow-8,400, Faster R-CNN ResNet50 attains 92.72% accuracy, 100% precision, 91.73% recall, 95.63% F1, and 86.25% mAP at 396 FPS. This robust performance benefits from clean annotations and controlled visual distributions, albeit with higher compute cost due to the two-stages detection and the used of Region Proposal Network (RPN). On the 625-image Roboflow subset, the Faster R-CNN ResNet50 model remains preeminent (92.42% accuracy, 81.00% mAP, 307 FPS). The ResNet50-based CNN consistently ranks between the two, reflecting stronger feature capacity than the standard CNN but lacking region-proposal mechanisms.Practically, the plain CNN suits low-cost on-device inspection, whereas Faster R-CNN is better matched to multi-object detection on curated datasets. Model selection should consider domain characteristics, target latency, available compute, and operational risk tolerance.

Keywords: Oil Palm, Ripeness Classification, CNN, ResNet50, Faster R-CNN, Deep Learning.