

SKRIPSI

**PERBANDINGAN KINERJA YOLOV11 DAN EFFICIENTDET DALAM
PENGENALAN KATEGORI SAMPAH BERBASIS CITRA**



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**PERBANDINGAN KINERJA YOLOV11 DAN EFFICIENTDET DALAM PENGENALAN KATEGORI
SAMPAH BERBASIS CITRA
SKRIPSI**

Sebagai salah satu syarat untuk menyelesaikan Program Strata-1 pada Jurusan Teknik Informatika Fakultas
Teknik Universitas Palangka Raya

Oleh

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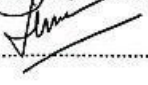
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PERNYATAAN

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KATA PENGANTAR

Puji syukur penulis panjatkan kehadiran Tuhan Yang Maha Esa atas berkat, rahmat, dan karunia-Nya sehingga penulis dapat menyelesaikan skripsi yang berjudul “Perbandingan Kinerja Yolov11 Dan Efficientdet Dalam Pengenalan Kategori Sampah Berbasis Citra”. Skripsi ini disusun sebagai salah satu syarat untuk memperoleh gelar Sarjana pada Program Studi Teknik Informatika, Fakultas Teknik, Universitas Palangka Raya.

Penelitian ini dilakukan untuk membandingkan kinerja YOLOv11-s dan EfficientDet-D1 dalam mengenali kategori sampah berdasarkan aspek akurasi, kecepatan, efisiensi komputasi, dan ketahanan terhadap kondisi citra yang mengalami gangguan.

Penulis menyadari bahwa skripsi ini masih memiliki keterbatasan dan belum sempurna. Oleh karena itu, kritik dan saran yang membangun sangat diharapkan untuk perbaikan di masa mendatang. Penulis berharap skripsi ini dapat memberikan manfaat dan menjadi referensi bagi penelitian selanjutnya dalam pengembangan teknologi pengenalan sampah berbasis kecerdasan buatan.

Palangka Raya, 19 Oktober 2026

Penulis



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ABSTRAK

Pengelolaan sampah membutuhkan proses pemilahan yang efektif. Penerapan deep learning dan computer vision dapat membantu mengenali kategori sampah secara otomatis. Penelitian ini bertujuan membandingkan kinerja YOLOv11-s dan EfficientDet-D1 berdasarkan akurasi, kecepatan, efisiensi, ketahanan terhadap gangguan citra, dan perbedaan waktu inferensi. Dataset yang digunakan adalah Garbage Classification v2 yang terdiri dari 12.259 citra RGB dan 10 kategori sampah. Dataset diadaptasi menggunakan full-image bounding box karena tidak memiliki anotasi bounding box, kemudian dibagi menjadi 70% data latih, 20% validasi, dan 10% data uji. Kedua model dilatih pada resolusi 640×640 piksel dan dievaluasi menggunakan metrik akurasi, kecepatan, efisiensi, robustness, serta paired t-test. Hasil menunjukkan EfficientDet-D1 lebih unggul dalam akurasi dengan mAP50–95 sebesar 0,9598 dan accuracy 91,7%, sedangkan YOLOv11-s memperoleh mAP50–95 sebesar 0,9390 dan accuracy 87,6%. YOLOv11-s sebesar 0,7138. Hasil paired t-test menunjukkan perbedaan waktu inferensi yang signifikan dengan p-value $4,28 \times 10^{-78}$. Berdasarkan hasil tersebut, EfficientDet-D1 unggul dalam akurasi dan robustness, sedangkan YOLOv11-s unggul dalam kecepatan dan ukuran model sehingga lebih sesuai untuk penerapan real-time. Penggunaan full-image bounding box menjadi keterbatasan karena mAP lebih merepresentasikan pengenalan kategori daripada pelokalan objek secara nyata.

Kata kunci: YOLOv11-s, EfficientDet-D1, sampah, deep learning, mAP, robustness.

COMPARISON OF YOLOv11 AND EFFICIENTDET PERFORMANCE IN IMAGE-BASED WASTE CATEGORY RECOGNITION

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ABSTRACT

Waste management requires an effective sorting process. The application of deep learning and computer vision can help automatically recognize waste categories. This study aims to compare the performance of YOLOv11-s and EfficientDet-D1 based on accuracy, speed, efficiency, robustness to image disturbances, and differences in inference time. The dataset used was Garbage Classification v2, consisting of 12,259 RGB images from 10 waste categories. Since the dataset did not contain bounding box annotations, it was adapted using a full-image bounding box and then divided into 70% training data, 20% validation data, and 10% test data. Both models were trained at a resolution of 640×640 pixels and evaluated using accuracy, speed, efficiency, robustness, and a paired t-test. The results show that EfficientDet-D1 achieved higher accuracy, with an mAP50–95 of 0.9598 and an accuracy of 91.7%, while YOLOv11-s achieved an mAP50–95 of 0.9390 and an accuracy of 87.6%. YOLOv11-s was faster, achieving 38.5 FPS with a latency of 26.0 ms, compared to EfficientDet-D1 at 23.0 FPS and 43.5 ms. EfficientDet-D1 also showed better robustness, with an mPC of 0.7604 compared to 0.7138 for YOLOv11-s. The paired t-test showed a significant difference in inference time, with a p-value of 4.28×10^{-78} . Based on these results, EfficientDet-D1 performed better in accuracy and robustness, while YOLOv11-s performed better in inference speed and model size, making it more suitable for real-time applications. The use of a full-image bounding box is a limitation because the mAP results primarily represent waste category recognition rather than actual object localization.

Keywords: *YOLOv11-s, EfficientDet-D1, waste, deep learning, mAP, robustness.*

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