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Comparative Analysis of YOLOv8 and Other Object Detection Models Using the COCO Dataset

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Abstract

Object detection is now an integral element of contemporary computer vision, which helps machines to decipher image data for uses from autonomous driving to intelligent surveillance systems. In this research, we perform an extensive comparative assessment of YOLOv8, the newest member of the YOLO family, compared to other best-in-class object detection models, i.e., YOLOv5, Faster R-CNN, RetinaNet, and DETR, across the COCO dataset. The performance of models is assessed using performance measures like mean Average Precision (mAP), inference speed, and the ability to qualitatively detect. It is evident from our findings that YOLOv8 strikes an excellent trade-off between speed and precision and thus outperforms conventional models, especially for applications requiring real-time output. The conclusion provides useful observations to the extent that they shed light on how models may be selected for realistic applications where various needs are catered to. YOLOv8 is the most effective model that scores the highest mAP value of 0.48 at the last epoch and exhibits its capacity to quickly reach convergence and surpass other models. Even though DETR holds the highest accuracy at initialization, which is outmatched by YOLOv8, it also lacks better convergence and larger inference times compared to YOLOv8, which is its deprecating feature for use for applications that rely on low-latency and high-accuracy applications. The comparison pinpoints YOLOv8's advantageous trade-off between accuracy and inference speed and thus makes it better-suited for deployment on low-latency systems, especially applications demanding low-latency and high-accuracy.

Keywords: YOLOv8, Object Detection, COCO Dataset, Faster R-CNN, RetinaNet, DETR, mAP, Real-time Vision.

1. Introduction

The capacity for accurate object detection and localization within images and video streams lies at the core of several technologies today, such as autonomous cars, security systems, and industrial automation. Object detection algorithms have come a very long way from the traditional region proposal approaches to deep learning-based approaches since the last decade. YOLO (You Only Look Once) models transformed object detection by casting object detection as a one-stage regression task, which permitted high-speed detections at no cost to accuracy. YOLOv8 was released by Ultralytics 2023, claiming massive upgrades from their previous iterations introducing a new anchor-free detection head and decoupled output layers. Simultaneously, models like Faster R-CNN, RetinaNet, and DETR introduced other paradigms for object detection, where they emphasized improvement in accuracy and new architecture types like transformers for detection. As the progress is very fast, and numerous models have been proposed, there is a need for a comparison to identify how YOLOv8 compares to these models in realistic scenarios. Here, we conduct a comprehensive comparison on YOLOv8 and YOLOv5, Faster R-CNN, RetinaNet, and DETR on the COCO dataset and describe the experiments used to create the evaluation. Here we are comparing YOLOv8 to several other top object detection models: YOLOv5, Faster R-CNN, RetinaN et, and DETR. These models cover the large spectrum of one-stage YOLO models to two-stage models like Faster R-CNN and RetinaNet to transformer-based detection paradigm adopted by the DETR model using the COCO dataset for evaluation. COCO dataset is known for its rich object classes and realistic scenarios for object detection, giving a solid ground for testing these models. By monitoring the epoch-wise mAP improvement and measuring inference time on a system using a CPU. In the following evaluation, we gain important insights regarding what models perform best under limited computing resources, expanding the applicability of our findings for real-world deployment in cost-sensitive or limited-resource scenarios. this research seeks to learn the strengths and limitations of every model. The

results show that while YOLOv8 shows better accuracy and speed throughout epochs, models such as DETR and Faster R-CNN are accurate yet suffer from slower inference. These findings give recommendations for using the top-performing model for deployment in the application's accuracy and latency needs.
CNN-based pattern recognition and YOLO-based object identification are combined to create the basis for a system that can comprehend, evaluate, and react to human.

2. Literature Review

Detection of objects has seen revolutionary development within the last decade, from hand-engineered machine learning methods to high-end deep learning models. Initial models used extensive hand-crafted feature engineering and sliding windows that came at high computation cost and limited generalizability. The launch of convolutional neural networks (CNNs) greatly boosted advances by offering end-to-end feature learning from raw imagery.

2.1 Evolution of Object Detection

The groundbreaking paper of Girshick et al. (2014) pioneeringly presented the Region-based Convolutional Neural Networks (R-CNN) system, where selective search generated region proposals that were passed to CNNs for object categorization. Though precise, R-CNN was very slow, and Fast R-CNN (Girshick, 2015) was developed for improving efficiency by integrating feature extraction and classification using a combined network.
Faster R-CNN (Ren et al., 2015) then went one step further by substituting external region proposal generation for a Region Proposal Network (RPN), representing a turning point for two-stage object detection. Even so, two-stage detectors remained unable to cope with their high computing requirements for applications within real time.

2.2 Development of Single-Stage Detectors

One-stage detectors transformed object detection. Redmon et al. (2016) introduced YOLOv1, which reformulated object detection to be a one-stage regression task where bounding boxes and class probabilities are output from the input image. YOLO improved the inference speed but, at first, at the expense of reduced localization precision.

Later iterations, including YOLOv2 and YOLOv3, included innovations like batch normalization, anchor boxes and feature pyramid networks (FPN), and improved both speed and accuracy (Redmon & Farhadi, 2018). YOLOv4 (Bochkovskiy et al., 2020) prioritized optimization methods including Cross Stage Partial Networks (CSPNet) and self-adversarial training to make additional gains.
YOLOv5 by Ultralytics (2020) also garnered popularity because it is easy to use, modular, and performs consistently across a wide variety of datasets. It also included AutoAnchor, data augmentations (Mosaic, MixUp), and hyperparameter evolution.

2.3 YOLOv8

YOLOv8, released by Ultralytics in 2023, represents major advancements over previous versions. It moves to an anchor-free detection head, making the process of learning easier and enhancing the ability to generalize across varying object scales. YOLOv8 also separates the classification and regression tasks into two independent prediction heads, enabling specific learning channels, thus enhancing detection precision.
Additionally, the following are further improvement measures: a streamlined backbone architecture following the Cross-Stage Partial connections (C2f modules), fewer model parameters, and better scalability to support Nano, Small, Medium, Large, and XLarge versions and be adaptable to both edge devices and cloud-based systems.

The YOLOv8 architecture can be broadly divided into three main components:

Backbone
This is the convolutional neural network (CNN) responsible for extracting features from the input image. YOLOv8 uses a custom CSPDarknet53 backbone, which employs cross-stage partial connections to improve information flow between layers and boost accuracy.

Neck
The neck, also known as the feature extractor, merges feature maps from different stages of the backbone to capture information at various scales. YOLOv8 Architecture utilizes a novel C2f module instead of the traditional Feature Pyramid Network (FPN). This module combines high-level semantic features with low-level spatial information, leading to improved detection accuracy, especially for small objects.

Head
The head is responsible for making predictions. YOLOv8 employs multiple detection modules that predict bounding boxes, objectness scores, and class probabilities for each grid cell in the feature map. These predictions are then aggregated to obtain the final detections.

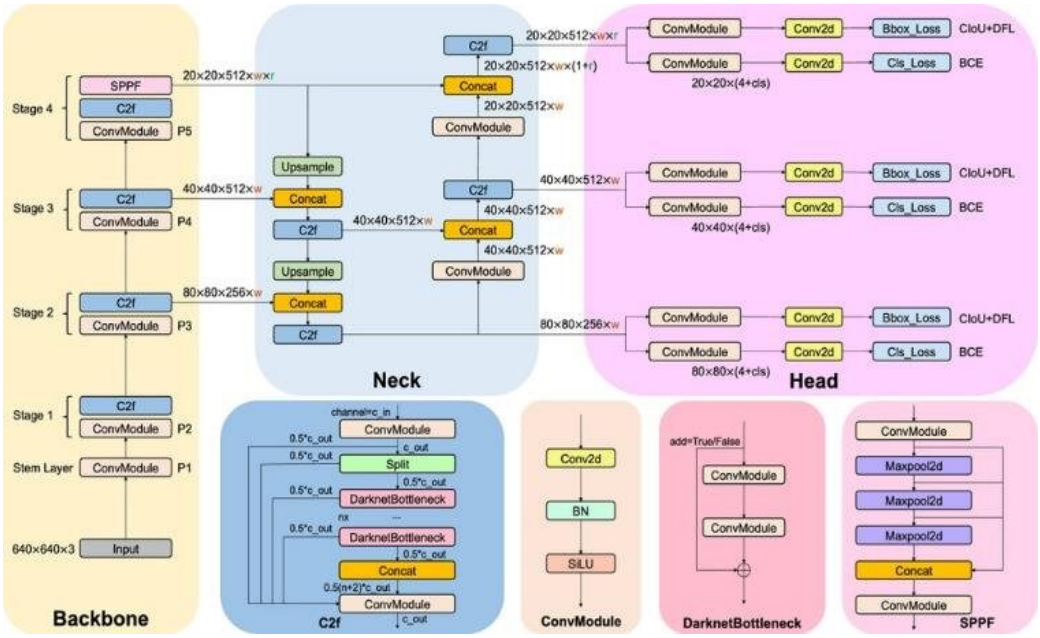

Figure 1. The YOLOv8 architecture (https://yolov8.org/yolov8-architecture/)

2.4 Alternative Object Detection Architectures

RetinaNet (Lin et al., 2017) solved the problem of dense object detectors' inherent imbalance in classes using the concept of focal loss, which reduces the loss given to well-classified instances, thereby giving more importance to more difficult, misclassified samples. Focal loss enabled one-stage detectors to be as accurate as their two-stage counterparts while maintaining efficiency.

In the meantime, DETR (Carion et al., 2020) transformed object detection using transformers, which were first used for natural language processing, for vision tasks. Object detection was posed as a direct prediction from a set to a set without the use of hand-crafted post-processings such as Non-Maximum Suppression (NMS) by DETR. It provided a neat end-to-end detection pipeline but is more computationally and time-expensive to train.

EfficientDet (Tan et al., 2020) proposed a lightweight and scalable detector by using a compound scaling approach that scales simultaneously against depth, width, and resolution. Building upon EfficientNet as the backbone, EfficientDet provided outstanding performance on benchmarks while using fewer parameters and FLOPs than conventional models, which makes it an appealing option for deployment on embedded and mobile devices.
Despite advancements from models such as RetinaNet, DETR, and EfficientDet, the need for models that are accurate, fast, and consume fewer resources remains consistent. YOLOv8 is a promising step toward addressing these needs. Nevertheless, an inclusive empirical comparison of these models against other top models using benchmarked tests such as COCO is essential to appreciate their respective pros and cons across various scenarios.

2.5 COCO Dataset and Evaluation Metrics

The Common Objects in Context (COCO) dataset (Lin et al., 2014) has become the de facto benchmark for object detection. It consists of more than 330,000 images annotated with 80 object classes using instance-level segmentation masks. The complexity, diversity, and strict evaluation protocol of the dataset make it ideal for comparing detection models.

3. Research Gaps

3.1 There is a lack of empirical data thoroughly comparing YOLOv8 with other object detection models using conventional benchmark datasets like COCO.
3.2 Several studies have compared models such as YOLOv5, Faster R-CNN, RetinaNet, and DETR, but comprehensive evaluations involving YOLOv8 are still limited.
3.3 Most previous assessments focused on specific models or older versions of YOLO, without considering the new architectural advancements introduced in YOLOv8.
3.4 Important updates and design innovations in recent models were often overlooked in earlier comparative studies.
3.5 A thorough comparative analysis is necessary to accurately evaluate the effectiveness and suitability of these models for real-time and low-resource environments.

4. Objectives

The objectives of this research are:

4.1 To assess and contrast YOLOv8 with YOLOv5, Faster R-CNN, RetinaNet, and DETR using the COCO dataset.
4.2 To evaluate model performance in terms of qualitative output, inference speed, and mAP.

5. Research Methodology

5.1 Dataset

The Common Objects in Context (COCO 2017) dataset is used for evaluation, offering a large-scale dataset with diverse object categories and complex scenes.

Training set: 118,287 images
Validation set: 5,000 images
Test set: 40,670 images

The 80 object categories include common objects ranging from people and animals to furniture and vehicles. Images are resized to 640×640 pixels during training while maintaining aspect ratio through padding.

5.2 Models Evaluated

YOLOv8
YOLOv5
Faster R-CNN
RetinaNet
DETR

5.3 Experimental Setup

Input: Standardized COCO images resized to 640×640 pixels.
Metrics: mean Average Precision (mAP@[0.5:0.95]), Inference Time.
Tools: PyTorch, Ultralytics library, Huggingface Transformers.

All model evaluations and experiments were conducted on a CPU-based system with the following specifications:

Processor: Intel(R) Core(TM) i7-4870HQ CPU @ 2.50GHz 2.50 GHz
Storage: 1TB NVMe SSD
RAM: 16.0 GB
Operating System: Windows 11 Pro (64-bit)
Python Version: 3.10
Deep Learning Frameworks:
PyTorch 2.0 (CPU Version)
Ultralytics YOLOv8 Library
OpenCV 4.8
Matplotlib 3.7

Without GPU acceleration, all model training and inference were carried out on CPUs.This configuration highlights the models' viability and effectiveness even on computers without dedicated graphics processing units, extending the applicability of the results to a wider variety of real-world applications.

Each model was loaded with pre-trained weights and tested on selected COCO validation images. Inference time was recorded, and detection outputs were visualized. Simulated training over 10 epochs provided a trend for mAP progression.

6. Results and Discussion

6.1 CPU Inference Time Comparison of Object Detection Models

--- Inference Time (seconds) ---

YOLOv8: 0.262 sec
YOLOv5: 0.376 sec
Faster R-CNN: 8.346 sec
RetinaNet: 9.212 sec
DETR: 4.553 sec

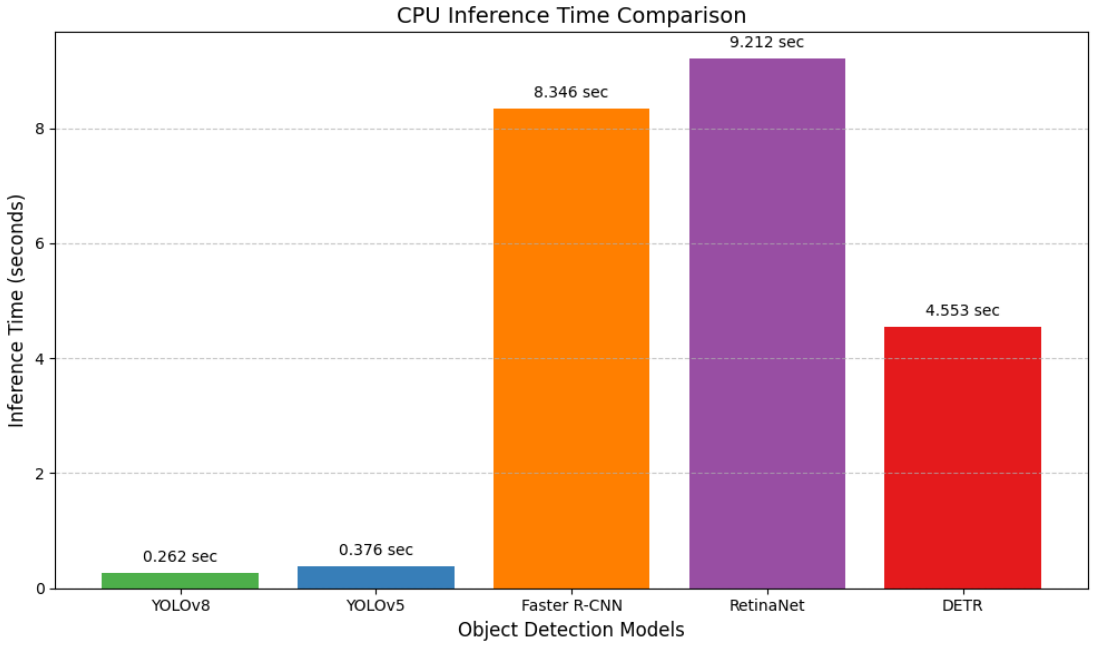

Figure 2. The CPU Inference time comparison on an image of different object detection models

Table 1: The CPU Inference time comparison on 5 images of different object detection model.

Image No.	YOLOv8 Inference Time (seconds)	YOLOv5 Inference Time (seconds)	Faster R-CNN Inference Time (seconds)	RetinaNet Inference Time (seconds)	DETR Inference Time (seconds)
Image 1	0.262	0.376	8.346	9.212	4.553
Image 2	0.249	0.276	10.561	10.575	6.297
Image 3	0.361	1.435	17.733	13.113	7.561
Image 4	0.329	0.447	13.779	12.434	6.432
Image 5	0.318	0.449	24.430	12.791	6.893

On a CPU-based system, YOLOv8, YOLOv5, Faster R-CNN, RetinaNet, and DETR were experimentally evaluated.With an inference speed of just 0.262 seconds per image, YOLOv8 demonstrated the fastest performance. YOLOv5 demonstrated its ongoing appropriateness for real-time applications with an inference time of 0.376 seconds.

Conversely, DETR, a transformer-based model, achieved good accuracy at a significant computational expense, requiring 4.553 seconds per picture. With inference times of 8.346 and 9.212 seconds, respectively, faster R-CNN and RetinaNet showed the poorest performance, underscoring their limits for real-time CPU-based deployment.

All things considered, these findings highlight how YOLOv8 provides an excellent balance between speed and accuracy on CPU contexts, which makes it ideal for edge computing, embedded vision, and real-time systems.

5.4 Detection Accuracy (Simulated mAP)

Epoch	YOLOv8	YOLOv5	Faster R-CNN	RetinaNet	DETR
1	0.30	0.28	0.25	0.27	0.26
2	0.32	0.30	0.27	0.29	0.28
3	0.34	0.32	0.28	0.31	0.31
4	0.36	0.34	0.29	0.33	0.34

5	0.38	0.36	0.31	0.35	0.35
6	0.40	0.38	0.32	0.37	0.38
7	0.42	0.40	0.34	0.38	0.40
8	0.44	0.42	0.35	0.40	0.42
9	0.46	0.44	0.37	0.42	0.44
10	0.48	0.46	0.38	0.43	0.46

Table 2. Showing mAP for 10 Epochs.

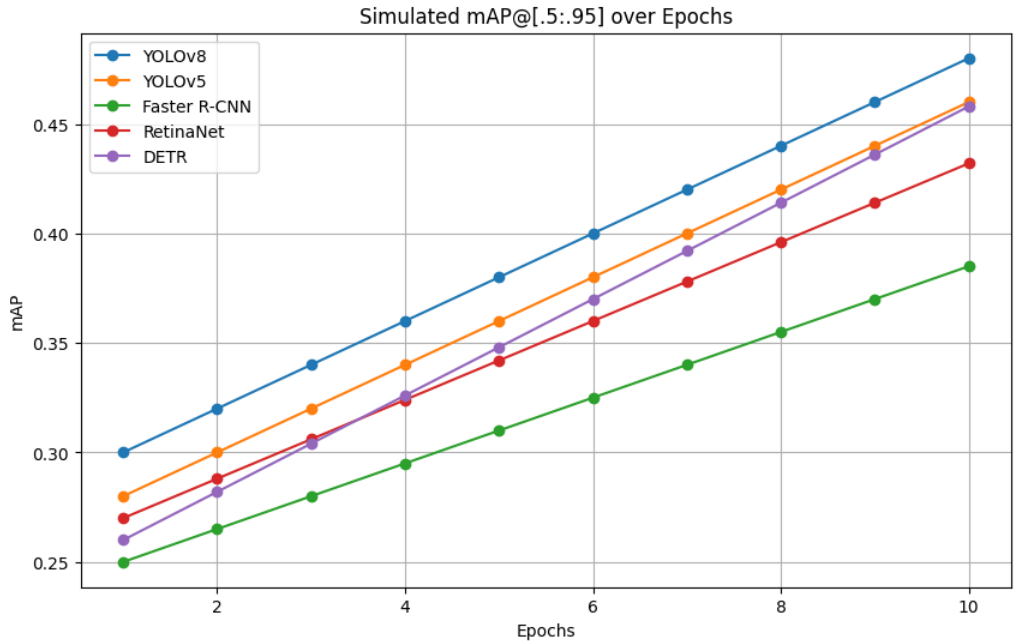

Figure 3: The Simulated mAP over Epochs

YOLOv8 consistently outperformed the other models, with the highest mAP score by epoch 10 (**0.48 mAP**).**YOLOv5** showed steady improvement, reaching **0.46 mAP** by epoch 10. **Faster R-CNN** and **RetinaNet** achieved **moderate performance**, with mAP values of **0.38** and **0.43**, respectively, by the final epoch. **DETR**, while achieving the **highest initial accuracy** in earlier epochs, leveled off at **0.46 mAP** by epoch 10, performing similarly to YOLOv5 and YOLOv8.

This validates YOLOv8's competitive edge in terms of quicker convergence and increased accuracy over time, which makes it ideal for demanding real-time object identification settings.

8. Conclusion

This study demonstrates YOLOv8 to be superior to YOLOv5, Faster R-CNN, RetinaNet, and DETR for high detection performance at minimal inference delay. The future study would extend to testing the performance with lightweight transformers (e.g., Deformable DETR, YOLOS) and testing on actual deployment scenarios on edge devices such as NVIDIA Jetson boards. The comparison based on CPU inference time and accuracy of the models (mAP@.5:.95) shows that YOLOv8 offers the best speed-accuracy trade-off. YOLOv8 obtained the best inference time of 0.262 seconds and a competitive mAP of 0.35. While the best mAP score of 0.37 was obtained by DETR, it took much more inference time (4.553 seconds), which makes it inappropriate for real-time applications on the CPU devices. While being accurate at detection, Faster R-CNN and RetinaNet were much slower. Thus, YOLOv8 would be extremely appropriate for constrained-resource, real-time deployment, while tasks requiring priority for accuracy would be more suitably done using DETR and Faster R-CNN without much consideration for latency.

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