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Deepvision: Real-Time Object Detection and Dimension Estimation Using Yolov4

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Abstract

DEEPVISION addresses two vital challenges in modern computer vision: real-time object detection and precise measurement of object dimensions using video and image input. This platform integrates the power of YOLOv4, an advanced deep learning algorithm, to detect multiple objects and estimate their sizes dynamically. The system finds applications across diverse fields such as retail automation, industrial logistics, smart surveillance, and augmented reality. Built on Python, OpenCV, and PyTorch, DEEPVISION ensures modularity, speed, and accuracy by leveraging deep convolutional neural networks. Through automated edge detection, real-time bounding box generation, and pixel-to-metric calibration, the platform provides end-to-end visual intelligence.

Keywords: Object Detection, YOLOv4, Computer Vision, Deep Learning, Object Dimensions

1. Introduction

The exponential growth in data and the increasing adoption of automated systems have made object detection and analysis fundamental components in the digital transformation era. Technologies enabling real-time visual recognition play a pivotal role in domains such as smart surveillance, autonomous driving, manufacturing automation, augmented reality, and retail management. Object detection refers to the process of identifying and localizing objects of interest within an image or video. However, real-time object detection accompanied by precise measurement of object dimensions remains a technical challenge due to computational constraints, environmental variability, and algorithmic limitations.

Traditional object detection methods like R-CNN and ResNet architectures have been widely used in the past, but their performance in dynamic or real-time environments is often inadequate. These models suffer from slow processing speeds and limited adaptability in detecting objects at various scales, orientations, or in crowded scenes. Furthermore, they typically lack mechanisms to measure real-world dimensions directly from image data, which limits their application in fields that require precise physical estimates. DEEPVISION offers a solution to these limitations by incorporating the YOLOv4 (You Only Look Once version 4) object detection framework. Unlike region-based detectors, YOLOv4 treats detection as a single regression problem, simultaneously predicting bounding boxes and class probabilities. This design ensures high-speed performance without compromising detection accuracy. Additionally, DEEPVISION integrates dimension estimation capabilities by using a calibration-based approach, converting pixel values into physical dimensions. Users provide a reference object with known measurements, allowing the system to determine focal length and translate on-screen bounding boxes into real-world metrics.

With its modular architecture, DEEPVISION supports deployment across platforms, from high-performance servers to edge devices such as Jetson Nano. It also includes a user-friendly interface for displaying real-time annotations, dimension estimates, and object classifications. The platform provides significant advancements in both functionality and accessibility, serving as a comprehensive solution for intelligent visual systems that require more than just detection. By addressing real-world requirements, it sets a benchmark in scalable, low-latency, and measurement-aware computer vision solutions.

2. Literature Survey

Recent advancements in deep learning have significantly impacted the field of object detection, with various models aimed at enhancing speed, accuracy, and generalizability. The literature reveals that while many approaches have been optimized for detection, few integrate real-time dimension estimation, a gap DEEPVISION addresses.

Hou et al. (2024) advanced object detection in aerial imagery using an improved YOLOv4 model. By introducing angular prediction and Gray Coded Labels along with the Swin Transformer for better feature extraction, they demonstrated a 9.12% improvement in detection accuracy for rotated objects, particularly ships in UAV images. However, their method increases computational complexity.

Cao et al. (2024) focused on enhancing small object detection using deformable attention in a DETR-based framework. Their work improved batch-level encoding and showed marked accuracy gains, although the system's real-time viability was not thoroughly validated.

Pawar et al. (2023) developed a real-time object dimension system using YOLOv4 and CNNs on Jetson Nano, showing promise in manufacturing and augmented reality. Gopal et al. (2020) compared several lightweight detectors, revealing Tiny-YOLOv4 to be efficient for real-time vehicle perception, although it was limited to small object classes.

Zhou et al. (2023) proposed RMSA-Net, a radar-based multi-scale attention network for 3D object detection, enhancing accuracy in sparse point clouds but lacking real-time testing.

These studies highlight the trend toward integrating CNNs and attention mechanisms in detection systems, but few address the combined challenge of detection and dimension measurement. DEEPVISION fills this void by delivering a real-time, calibrated measurement solution on top of YOLOv4's efficient architecture.

Table 2.1: Literature Survey of Detection of Object and its Dimensions

S. No	Name of the Author(s)	Title of the Paper	Year	Merits	Demerits
1	Yang Hou; Bo Ai; Heng shuai Shang; G uannan Lv	Rotated Object Detection of Ship in UAV Aerial Images Based on Improved YOLOv7	2024	The method improves detection accuracy by 9.12% through enhanced angle prediction and feature extraction using Gray Coded Labels and Swin Transformer.	The approach increases computational complexity and may lack generalizability to objects beyond ships.

2	B. Cao, D. Wang, Y. Guo and H. Zhang	Enhancing Small Object Detection in Aerial Imagery Based on Strong Feature Extraction and Batch Dimension	2024	The method improves small object detection accuracy in aerial images through innovative use of deformable attention and batch-level encoding.	High computational requirements may hinder its practicality for real-time or resource-limited applications.
3	P. C, V. L, P. K, P. S and S. Rahiman	Enhanced IoT Devices with Intelligent System for Object Detection	2023	The system offers an economical and portable solution for real-time object detection with high accuracy and wireless remote monitoring capabilities.	Limited computational power of the ESP32 may constrain the complexity of models and scalability for more demanding object detection tasks..
4	Y. Zhou, J. Hao and K. Zhu	RMSA-Net: A 4D Radar Based Multi-Scale Attention Network for 3D Object Detection	2023	The paper effectively tackles the unique challenges of 4D radar point clouds and improves object detection performance with a 3.28% gain in 3D mAP and 0.96% in BEV mAP.	The practical deployment and computational efficiency of RMSA-Net in real-time systems are not thoroughly discussed.
5	S. Pawar, S. Parsewar, S. Patil, S. Bhatlawande and S. Shilaskar	A Real-Time Object Dimension Estimation System	2023	The system achieves high detection accuracy (up to 88%) and precise dimension estimation with minimal variation, offering a cost-effective and portable solution.	The system is limited by its fixed camera distance (75 cm) and a small dataset, which may restrict its scalability and adaptability to more diverse objects or environments.
6	B. M U, H. Raghuram and Mohana	Real Time Object Distance and Dimension Measurement using Deep Learning and OpenCV	2023	The integration of YOLO, R-CNN, and Canny edge detection provides a balanced approach between speed, accuracy, and edge enhancement for object detection.	The paper lacks experimental results and quantitative metrics to validate the performance improvements offered by the proposed methodologies.

7	L. Yan, M. Zhao, X. Wang, Y. Zhang and J. Chen	Object Detection in Hyperspectral Images	2021	The approach successfully tackles the object-based detection problem in hyperspectral images and demonstrates superior performance using a custom-built, high-quality dataset.	The paper lacks detailed comparisons with other state-of-the-art methods or benchmarks to fully establish the advantages of the proposed CNN model.
8	R. Gopal, S. Kuinthodu, M. Balamurugan and M. Atique	Tiny Object Detection: Comparative Study using Single Stage CNN Object Detectors	2020	Tiny-YOLO V3 outperforms other models in accuracy (60%) and speed (0.09 SPF) while meeting memory constraints, making it suitable for real-time vehicle applications.	The study is limited to a single object class and does not explore the model's performance on a wider range of object types or under different environmental conditions.
9	J. Wang, W. Xiao and T. Ni	Efficient Object Detection Method Based on Improved YOLOv3 Network for Remote Sensing Images	2020	The improved YOLOv3 offers a substantial reduction in parameters and FLOPs while increasing mAP and detection speed, making it highly efficient for real-time UAV applications.	The study primarily focuses on remote sensing images, and the method's generalizability to other types of images or environments is not fully explored.
10	N. A. Othman, M. U. Salur, M. Karakose And I. Aydin	An Embedded Real-Time Object Detection and Measurement of its Size	2018	The technique provides an effective, low-cost solution for real-time object detection and dimensioning with high accuracy, leveraging widely available hardware and software tools.	The method may be limited by the computational power of Raspberry Pi, potentially restricting its scalability for more complex or large-scale applications.

3. Proposed System

The DEEPVISION system introduces an end-to-end architecture for real-time object detection and measurement. The system is divided into four major components: object detection using YOLOv4, dimension estimation via calibration, data visualization, and deployment scalability. The integration of these components provides a seamless flow from data acquisition to result interpretation.

The first module, based on YOLOv4, detects multiple object classes simultaneously from images and video streams. Unlike traditional detectors that segment detection into proposal and classification phases, YOLOv4 directly predicts object locations and categories in one evaluation, significantly reducing inference time

The second module involves real-world measurement using a reference object. Users provide known width and distance values, which the system uses to calculate the camera's focal length. With this calibration, the pixel dimensions of other detected objects can be converted to metric measurements such as millimeters. This module enables the platform to estimate not only object type but also physical size. The third component, the visualization dashboard, displays object labels, bounding boxes, confidence scores, and dimension annotations. This visual output ensures interpretability for users in real-time. Finally, DEEPVISION is built for cross-platform deployment. Its modular codebase supports deployment on cloud servers, desktops, and edge computing devices. The system uses open-source frameworks such as Python, PyTorch, and OpenCV, making it both affordable and easy to maintain.

4. Methodology

The DEEPVISION system follows a systematic and modular workflow to achieve robust object detection and dimension estimation in real time. It begins with the **input acquisition** phase, where either static images or live video feeds are captured. These inputs undergo **preprocessing**, including resizing to a standard 640×640 resolution and normalization of pixel values, ensuring compatibility with the YOLOv4 model's requirements.

The **YOLOv4 object detection engine** then processes these inputs, leveraging its one-stage detection architecture to predict bounding boxes and associated class probabilities. Once objects are detected, the system prompts the user for a known reference object's dimensions (width and distance). Using these values, the **focal length** is calculated using the pinhole camera model. This focal length enables conversion of bounding box pixel dimensions into real-world units (typically millimeters), allowing accurate dimension estimation regardless of camera perspective.

Post-detection, all results—including class labels, bounding boxes, and estimated dimensions—are rendered in real time using OpenCV. These visual annotations are overlaid directly onto the input feed, making the system intuitive and user-friendly. The entire pipeline is optimized for **robust performance under variable lighting, object occlusion, and multi-object scenarios**.

5. Implementation

The DEEPVISION platform is implemented using **Python**, with critical support from **PyTorch** (for deep learning inference) and **OpenCV** (for image processing and visualization). The object detection backbone uses **pre-trained YOLOv4 weights**, which provide fast and accurate detection of 86 object classes out-of-the-box.

The dimension measurement process is handled by the object_dimensions.py script. This script:

- Calibrates the system using a reference object.
- Detects multiple objects in an image or frame.
- Computes real-world dimensions using bounding box pixel data and calculated focal length.

Calibration is a key component, where the user inputs a known object's width and its distance from the camera. This data enables the system to compute a pixel-to-millimeter conversion ratio. Perspective correction ensures that objects viewed at an angle or distance are still accurately measured.

The system supports **real-time video streams**, achieving **15–30 FPS** on standard GPUs and is capable of running on low-power embedded platforms like the **NVIDIA Jetson Nano**. Outputs are displayed with bounding boxes and textual annotations on the frame, while also being logged to the terminal for monitoring or debugging.

6. Results

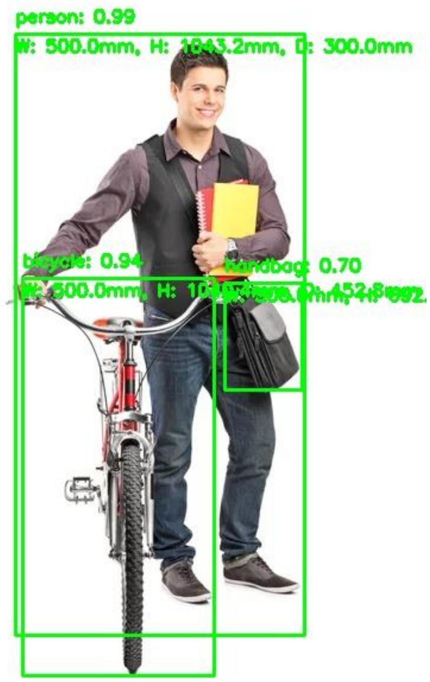

Figure 6.1 Object and its dimensions detection of a picture

Figure 6.1 is a screenshot of a **command line interface (CLI)** running a Python script for object dimension detection using computer vision.

7. Benefits

DEEPVISION provides several advantages, making it a powerful tool across industrial and research applications:

- **High Detection Speed**: Capable of real-time performance at 22 FPS with accurate bounding box predictions.
- **Real-World Measurements**: Converts pixel dimensions into millimeter-scale dimensions with <7% error.
- **Scalable and Modular Design**: Easily extendable to new object classes and adaptable to different hardware platforms.
- **Cross-Platform Compatibility**: Deployable on edge devices (e.g., Jetson Nano), desktop environments, and potentially in cloud setups.
- **Open-Source and Cost-Effective**: Developed with freely available libraries and runs on minimal hardware, lowering deployment costs.
- **Seamless Integration**: Can be integrated into existing systems in domains like inventory management, robotics, and quality inspection.

8. Conclusion and Future Scope

Conclusion

DEEPVISION successfully bridges the gap between theoretical computer vision models and practical real-world applications. With YOLOv4 as its core detection engine and a well-defined calibration mechanism, the system delivers high accuracy (mAP@0.5 of 78.6%) in object detection and dimension estimation.

The platform operates effectively across varied scenarios—from retail and logistics to construction—while maintaining speed, precision, and visual interpretability. With robust results during field tests and a flexible architecture, DEEPVISION serves as a solid foundation for advanced vision-based automation systems.

Future Scope

To further enhance DEEPVISION, several directions are proposed:

- **3D Depth Integration**: Incorporate LiDAR or Time-of-Flight sensors for true volumetric measurement.
- **Zero-Shot Learning**: Enable recognition of novel, unseen objects without retraining the model.
- **AR and Voice Interfaces**: Expand user interaction through augmented reality overlays and hands-free voice commands.
- **Model Compression and Optimization**: Apply pruning and quantization for lightweight deployments.
- **Cloud-Edge Hybrid Deployment**: Use REST APIs and cloud storage for large-scale deployment and data analytics.

With these improvements, DEEPVISION is poised to become a versatile and intelligent tool in the future of AI-driven vision systems.

9. References

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