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BarBeR: A Barcode Benchmarking Repository



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1 – Introduction



Barcodes have been essential for automatic data capture for over seven decades, playing a critical role in industries such as retail, manufacturing, and logistics.

Research in this field is hindered by a lack of public datasets and available code implementations. 2 – Dataset

Barcode types: 19 classes, including linear (Code 128, UPC) and 2D (QR Code, DataMatrix).

The dataset includes images captured under various conditions, such as varying lighting, noise, and obstructions.

Annotations: VGG format with polygon shapes, barcode type,

To tackle these challenges, we introduce BarBeR—an open-source benchmark for barcode detection paired with a public dataset of 8,748 annotated barcode images.



Link to Link to Repository Dataset

pixels-per-module (PPM), and encoded strings.



3 – Benchmark Framework

BarBeR supports a plethora of algorithms that could be tested with different tests and metrics:

 Available Algorithms: supports four traditional CV methods (Gallo et al., Soros et al., Yun et al., Zamberletti et al.) and three deep learning frameworks (Torchvision, Ultralytics and Detectron2).

4 – 1D Barcode Localization

The framework allows for graph visualization of different metrics.

All the available algorithms support 1D barcode localization.



- Available Tests: single-class localization (1D or 2D), multi-class detection, time measurement.
- Available Metrics: Precision, Recall, F1 Score, mAP@IoU.



The test was performed with 5-fold crossvalidation

Deep-learning methods have higher F1 scores, with RT-DETR achieving the highest score.

Yun et al. is the best among traditional CV methods.



F1-scores for 1D Barcode Localization.

5 – Multi-class Detection

Multi-class detection is supported only by deep-learning models. Models are tested at different image resolutions.



6 - Time measurement

Algorithms were tested on a high-end PC and a Raspberry PI 3B+.

This highlights significant differences in processing times based on the hardware and method used.





Detection Method	Times on PC (ms)			Times on Raspberry PI (ms)	
	Single-Thread CPU↓	Multi-Thread CPU ↓	GPU↓	Single-Thread CPU↓	$\begin{array}{c} \text{Multi-Thread} \\ \text{CPU} \downarrow \end{array}$
Gallo <i>et al</i> .	1.63	-	_	53.45	-
Soros <i>et al.</i>	11.25	-	-	397.53	-
Zamberletti <i>et al.</i>	48.20	-	-	1360.23	-
Yun <i>et al.</i>	7.59	-	-	146.31	-
Zharkov <i>et al.</i>	25.85	5.97	1.45	2120.43	1949.08
YOLO Nano	64.99	17.40	18.66	3034.27	1803.09
YOLO Medium	478.92	51.36	23.91	20083.87	15813.46
RT-DETR	985.41	141.06	37.55	39882.45	33224.15
Faster R-CNN	1271.93	237.91	30.27	∞	∞
RetinaNet	1124.11	105.20	36.00	∞	∞

Conclusions: most methods can run in real-time on PCs, but mainstream deep learning architectures remain too slow for many embedded applications.