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BarBeR: A Barcode Benchmarking Repository Implementation and Reproducibility Notes

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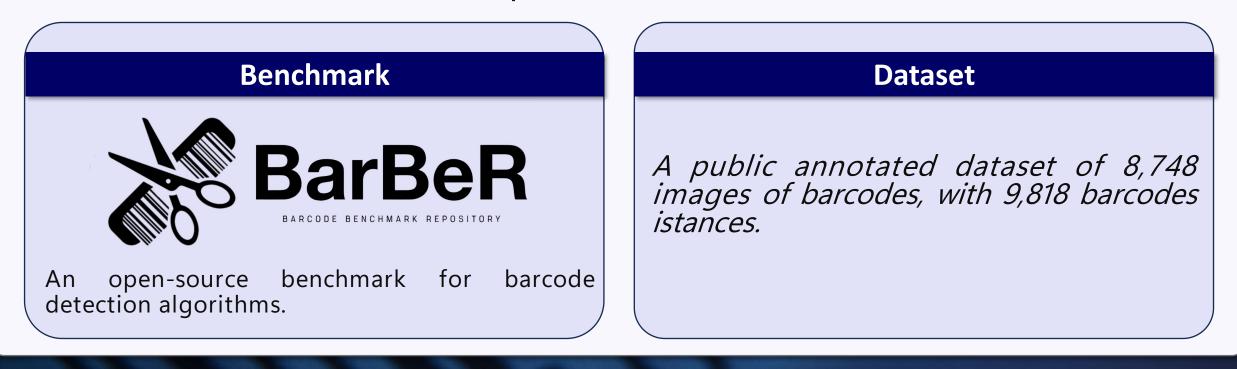






The BarBer Project

- Barcodes are a cornerstone of automatic data capture, critical in retail, manufacturing, and logistics.
- However, research in this field is hindered by the limited availability of public datasets and code implementations.
- To address these issues, we present :



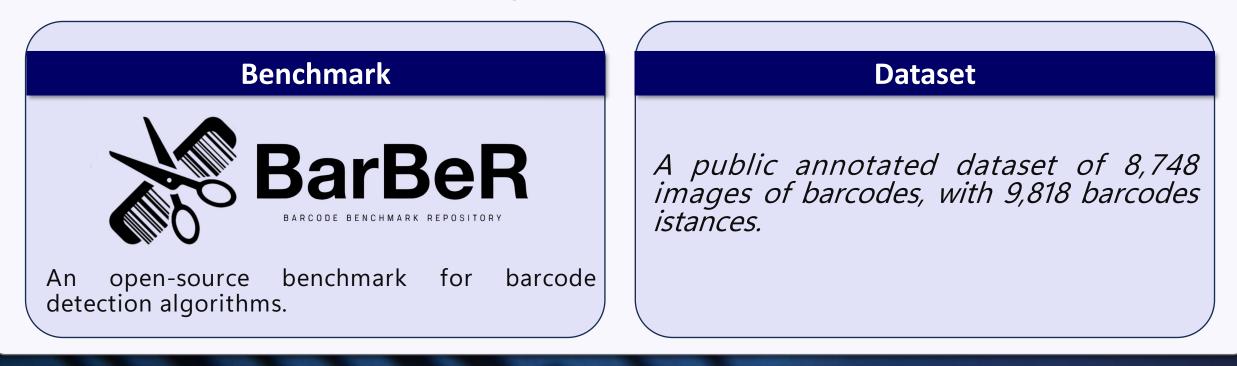
Dataset

- **Barcode types:** 19 classes, including linear (Code 128, UPC) and 2D (QR Code, DataMatrix).
- Annotations: VGG format with polygon shapes, barcode type, pixels-per-module (PPM), and encoded strings.
- A total of 8748 images, with 8062 instances of 1D barcodes and 1756 2D barcodes.



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Benchmark



- 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).
- Available Tests: Single-Class Localization (1D or 2D), Multi-Class Detection, Time Measurement.
- Available Metrics: Precision, Recall, F1 Score, mAP@IoU.



Available Algorithms

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BARCODE BENCHMARK REPOSITORY

- Some methods work only for 1D, others for both 1D and 2D
- Some methods support multi-ROI detection
- As mainstream architectures we tested YOLO, Faster RCNN, RetinaNET and RT-DETR

Algorithm	File	1D Detection	2D Detection	Multi-Label	
Gallo et al. [1] gallo detector.py		1	×	×	
Soros et al. [2]	soros detector.py	1	1	×	
Yun et al. [3]	yun_detector.py	1	×	×	
Zamberletti et al. [4]	zamberletti detector.py	1	×	1	
Zharkov et al. [5]	zharkov detector.py	1	1	1	
Ultralytics Models	ultralytics detector.py	1	1	1	
Detectron2 Models	detectron2_detector.py	1	1	1	
Pytorch Models	$pytorch_detector.py$	1	1	1	

References:

[1] Gallo, Orazio, and Roberto Manduchi. "Reading 1D barcodes with mobile phones using deformable templates." *IEEE transactions on pattern analysis and machine intelligence* 33.9 (2010): 1834-1843.

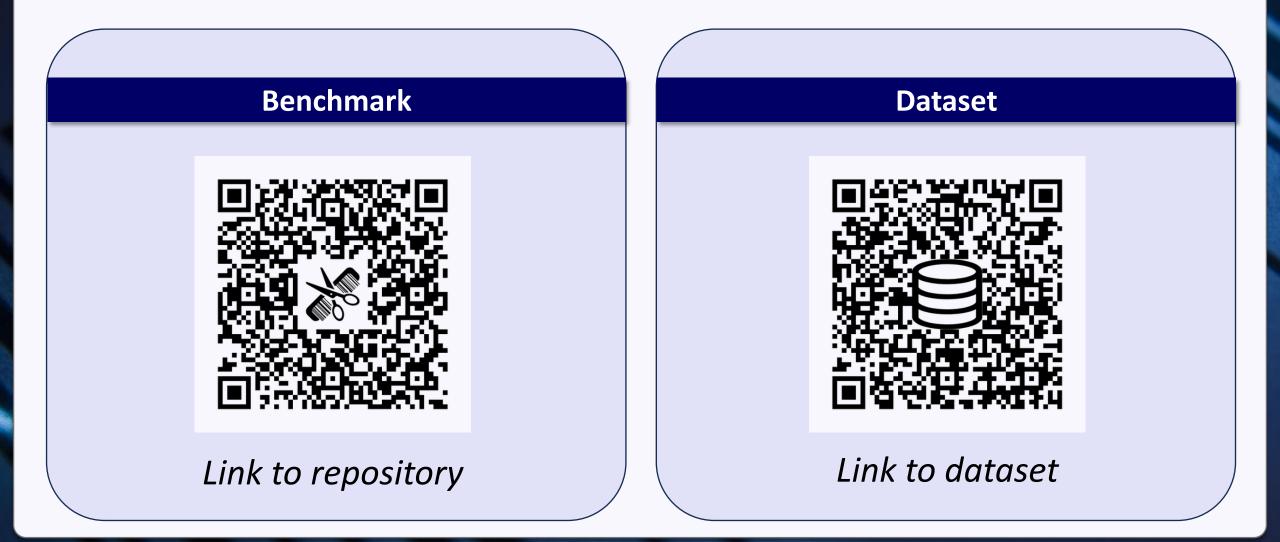
[2] Sörös, Gábor, and Christian Flörkemeier. "Blur-resistant joint 1D and 2D barcode localization for smartphones." Proceedings of the 12th International Conference on Mobile and Ubiquitous Multimedia. 2013.

[3] Yun, Inyong, and Joongkyu Kim. "Vision-based 1D barcode localization method for scale and rotation invariant." TENCON 2017-2017 IEEE Region 10 Conference. IEEE, 2017.

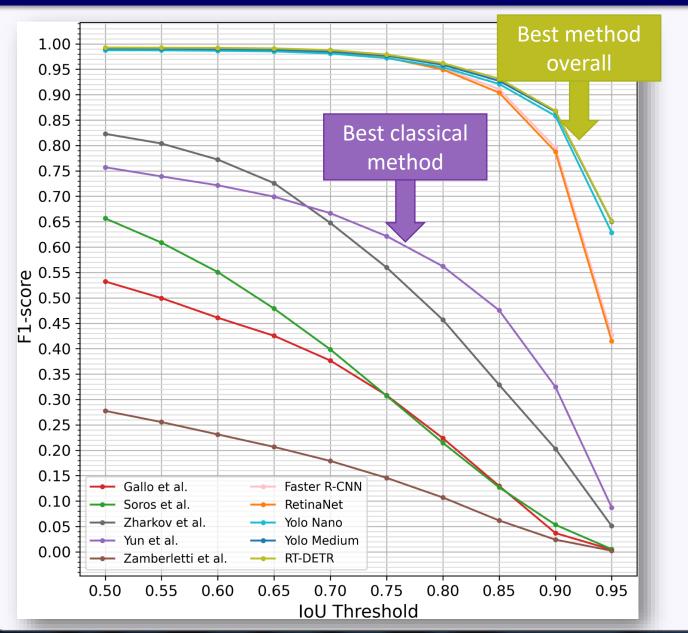
[4] Zamberletti, Alessandro, et al. "Neural 1D barcode detection using the Hough transform." Information and Media Technologies 10.1 (2015): 157-165.

[5] Zharkov, Andrey, and Ivan Zagaynov. "Universal barcode detector via semantic segmentation." 2019 International Conference on Document Analysis and Recognition (ICDAR). IEEE, 2019.

• Both Benchmark and dataset are available on GitHub.

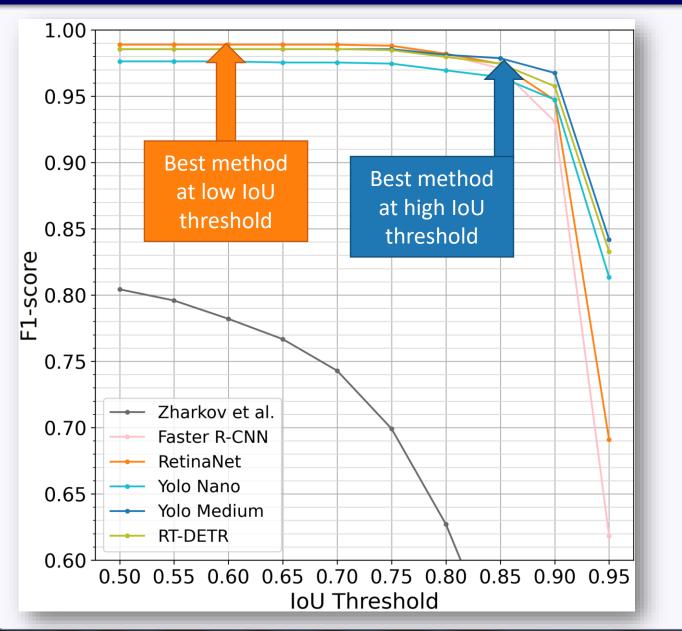


1D Localization



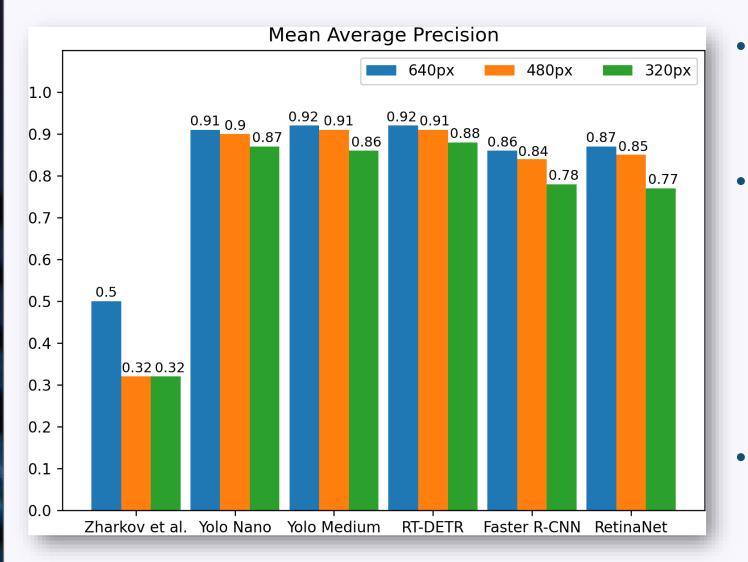
- 1D Barcodes can be located with all proposed methods.
- In this first test, only images with a single ROI are considered.
- The metric used is the F1-score considering an IoU threshold of 0.5.
- Images have been resized to have their longest edge of 640 pixels.

2D Localization



- Soros et al. is the only classical method that also supports 2D barcode detection.
- But gets an F1-score of just 0.141, and thus was not included in the graph.
- The leaderboard of deep-learning models remains more or less the same, but Faster-RCNN and RetinaNet perform better this time.

Multi-Class Detection



- Only deep-learning methods support multi-class detection.
- The test was conducted at 3 different resolutions for the longest edge of the images:
 - 640 Pixels
 - 480 Pixels
 - 320 Pixels
- The performance metric used is the mAP[0.5:0.95].

Time measurement

- Algorithms were tested on a high-end PC and a Raspberry PI 3B+. Images were scaled to have the longest edge of 640.
- This highlights significant differences in processing times based on the hardware and method used.

	Times on PC (ms)			Times on Raspl	Times on Raspberry PI (ms)	
Detection Method	Single-Thread CPU↓	$\begin{array}{c} \text{Multi-Thread} \\ \text{CPU} \downarrow \end{array}$	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	1 1 2 4.11	105.20	36.00	∞	∞	

Repository Setup

- Git clone the repository.
- Install the needed C++ libraries: OpenCV, OpenCVcontrib, Boost.
- Download the dataset. Unzip the file and put the 2 folders Annotations and dataset in the repository.
- Build the repository using Cmake:

mkdir build
cd build
cmake ..
cmake --build .



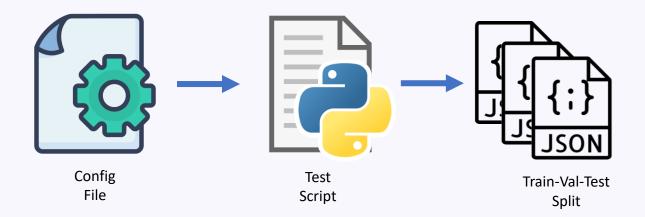
> algorithms > annotations > build > config > dataset > Gallo2011-Soros2013-Yun2017 > python > results > scripts > Tekin2012 > Zamberletti2013 Zharkov2019

The repository should have this structure after the setup.



- To run a test, COCO annotations must be divided into train.json, val.json, and test.json.
- A YAML configuration file is used to specify the annotation split settings, including the files and annotations to use, train-test split size, and whether K-fold cross-validation is applied.
- To run the annotation convertion:

python3 python/generate_coco_annotations.py -c
./config/generate_coco_annotations_config.yaml -k 0



Single-Class and Multi-Class Localization

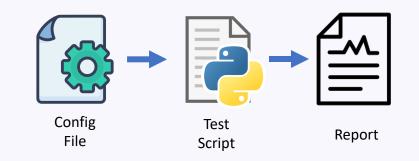
 The Python script that runs the Single-Class detection test is test_single_class.py: inputs are a configuration file and a path pointing to where the output report will be saved.

python3 python/test_single_class.py -c
./config/test_config.yaml -o ./results/test_results.yaml

 The script test_multiclass.py runs multi-class detection, taking a configuration file and an output path for the report.

python3 python/test_multiclass.py -c
./config/test_config.yaml -o ./results/test_results.yaml

• The output file will be a YAML file with all the metrics measured during the test.



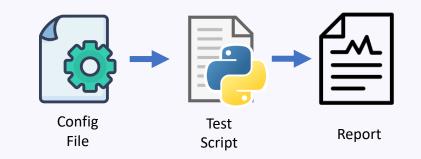
coco annotations path: ./annotations/COCO/ longest edge resize: 640 single ROI: true bins: [-100, 0, 0.5,1.0,1.5,2.0,2.5,3.0,3.5,4.0,100] algorithms: args: imgsz: 640 model path: ./Saved Models/yolon 640 0.pt class: YOLO detector library: ultralytics detector name: Yolo Nano args: imgsz: 640 model_path: ./Saved Models/yolom 640 0.pt class: YOLO detector library: ultralytics detector name: Yolo Medium

Example of configuration file for 1D localization.

- The script time_benchmark.py measures the time required to run the localization algorithms.
- It is possible to measure the algorithms' performance on a single core or multiple cores as well as on GPU.
- As for the previous test scripts, the required inputs are a path to a configuration file and a path to the destination folder for the generated report.

• To run the test:

python3 python/time_benchmark.py -c
.config/timing_config.yaml -o ./results/timing_results.yaml

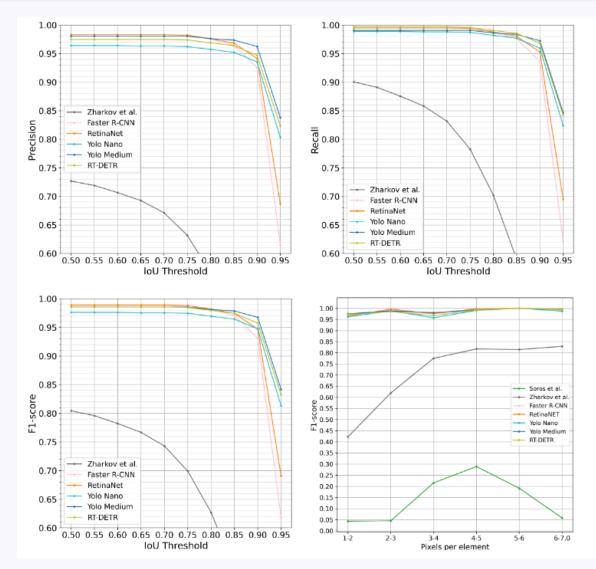


<pre>coco_annotations_path: ./annotations/COCO/</pre>
define: &img_size 640
<pre>longest_edge_resize: *img_size</pre>
num_repeats: 3
num_threads: 1
step: 32
define: &device 'cpu'
algorithms:
- args:
<pre>model_path: ./Saved_Models/zharkov_640_0.pt</pre>
device: *device
class: Zharkov_detector
library: zharkov_detector
name: Zharkov

Example of configuration file.

Graph Visualization

- The repository has two scripts for graph generation:
 - single_class_graphs.py: for single-class localization tests
 - multi_class_graphs.py: for multi-class detection tests
- Running the scripts will automatically generate .png files of the graphs.



Example of generated graphs

- To test a new algorithm, you have to define a new file in the algorithms folder.
- Define a class with the implementation of the algorithm. To ensure compatibility, the new class should inherit from the abstract class "BaseDetector".
- A detector must have at least these two methods: detect and get_timing.

```
# Defining the new class inside algorithms/new_algorithm.py
from detectors_abs import BaseDetector

class NewDetector(BaseDetector):
    def __init__():
        ...
    def detect(self, img):
        ...
    def get_timing(self):
        ...
```

BarBeR fosters innovation as an open and reliable tool for evaluating barcode detection. We invite contributions to drive advancements in automatic data capture technology.



Link to repository

Thank You!



Link to dataset