Ewaste-Net

Everything it touches turns into gold.

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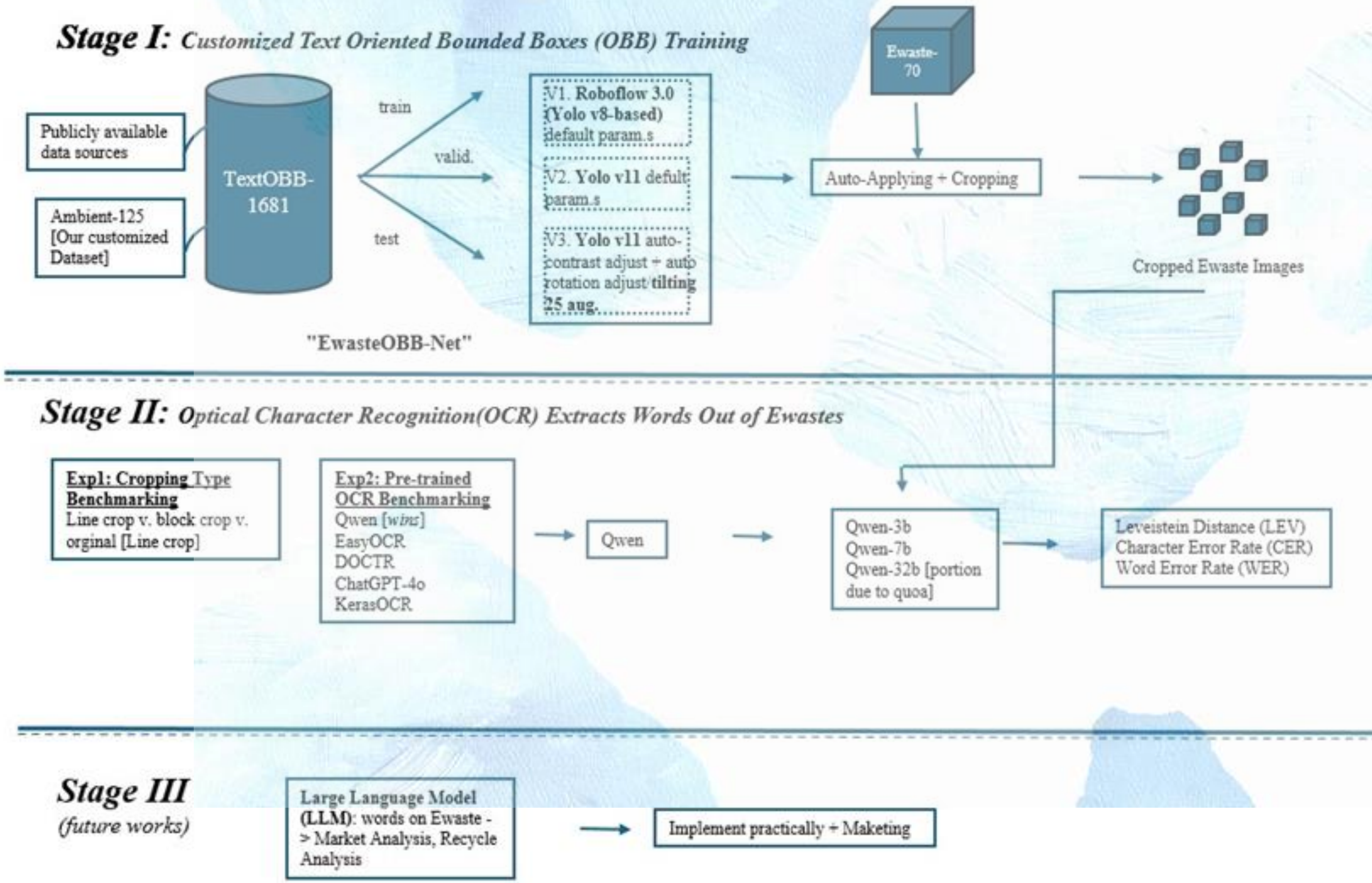
62 million tonnes of e-waste was produced in 2022.

22.3% of the year's e-waste mass was documented (UNITAR 2024).

Numerous Legislations are put forward towards Ewaste recycling. (EU 2024)



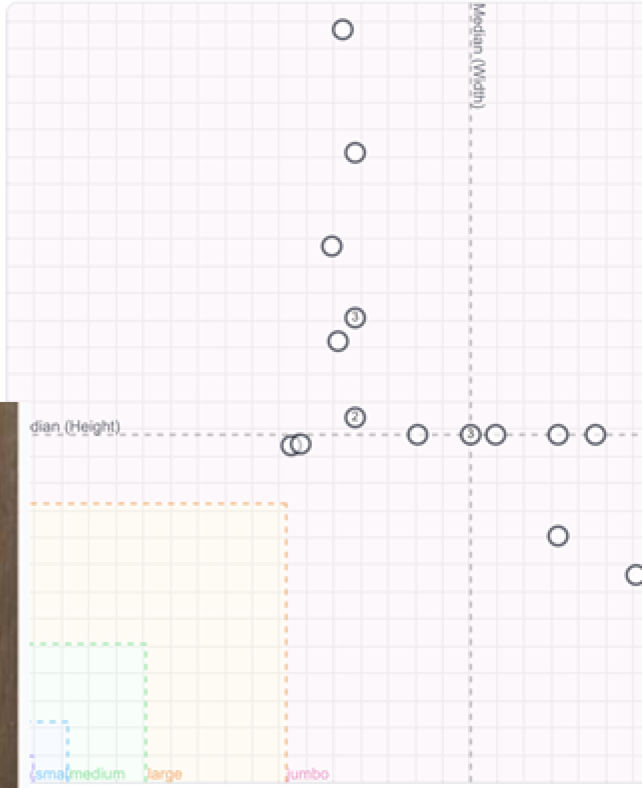
1. **Datasets:**
   - *Ambient-125*
   - *Ewaste-70*
   - *TextOBB-1681*

2. **Stage I.**
   - *Yolo models*
   - *Auto Cropping*
   - *Future fine tuning tips*

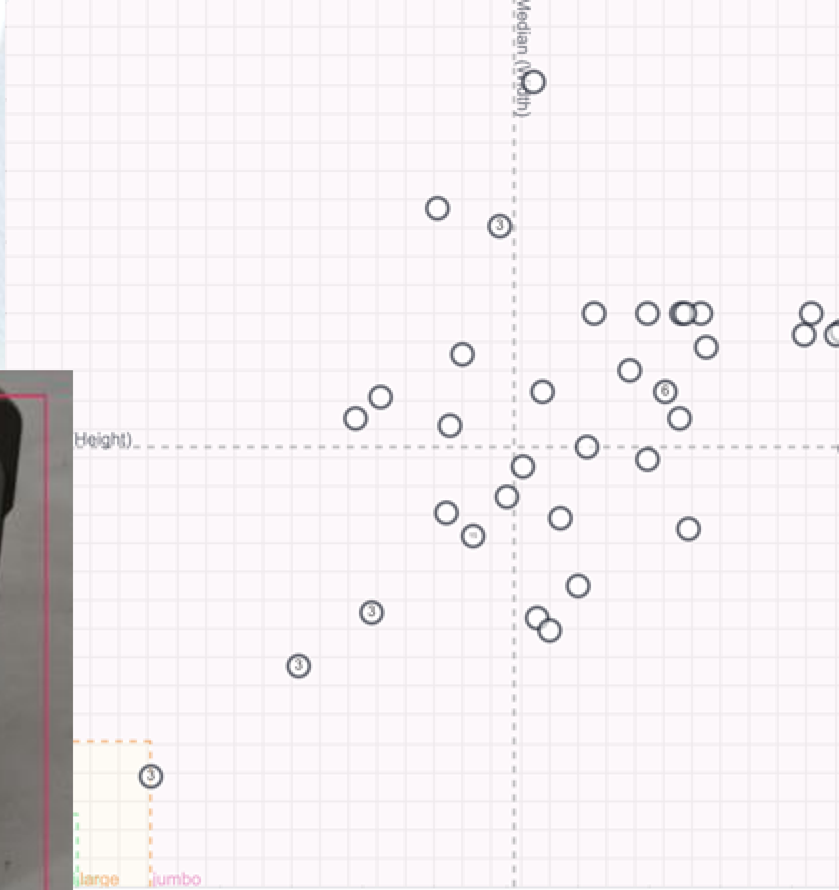
3. **Stage II.**
   - *Two experiments determines OCR and Crop types*
   - *Qwen Implementations*
   - *Results*

- **4. Future Expectations** *and a message to D3.*

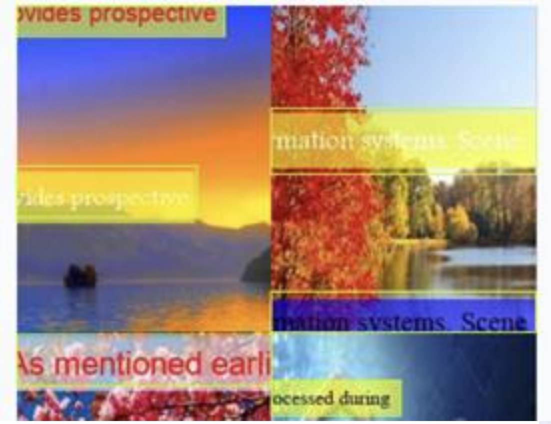
Datasets: Ambient-125

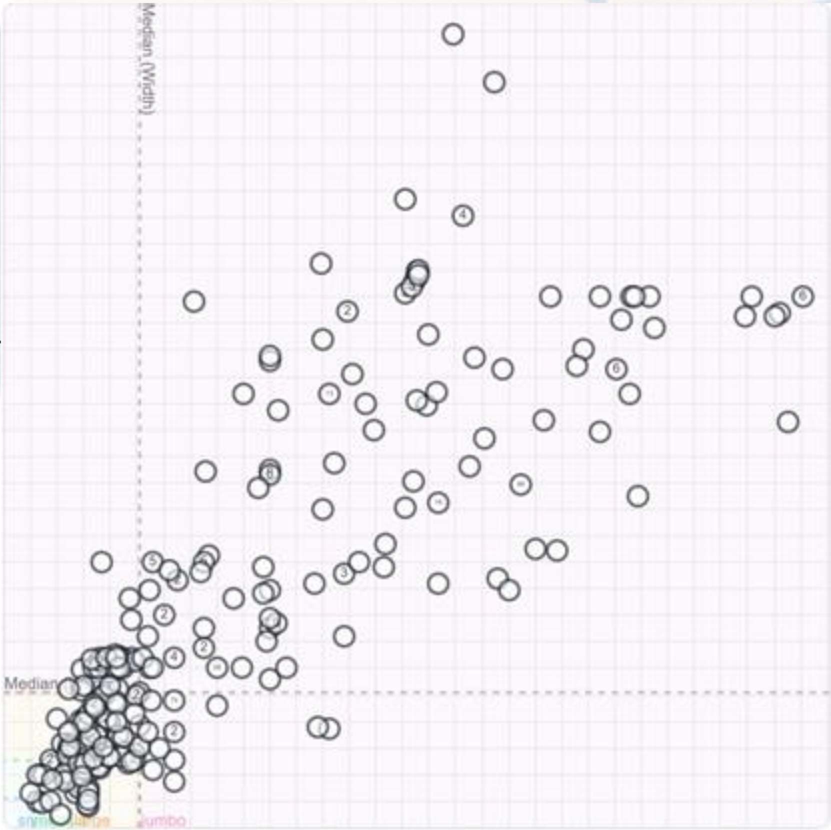


Datasets: Ewaste-70



Datasets: Text0bb-1681



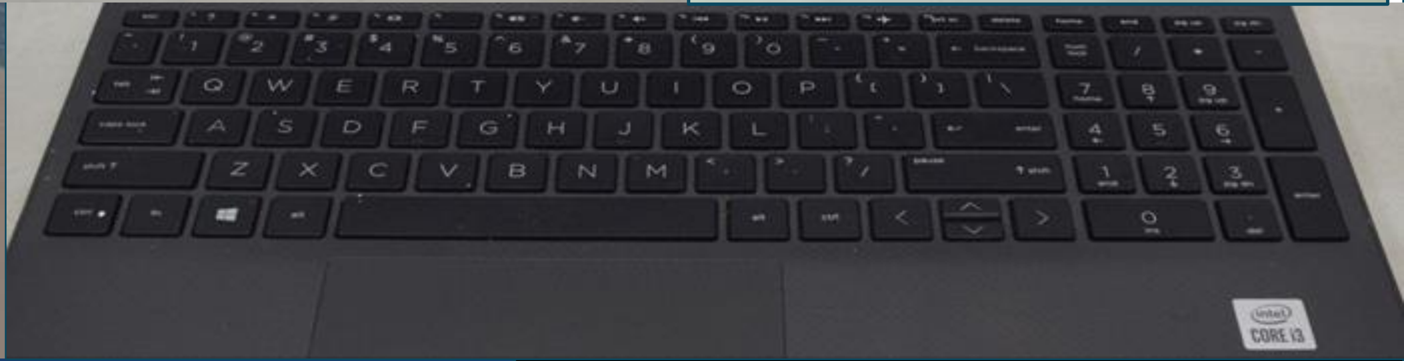


1681 images, combining ours, D3 dataset, and publicly available datasets

STAGE I. EwasteOBB-NET:

Sift, Filter texts

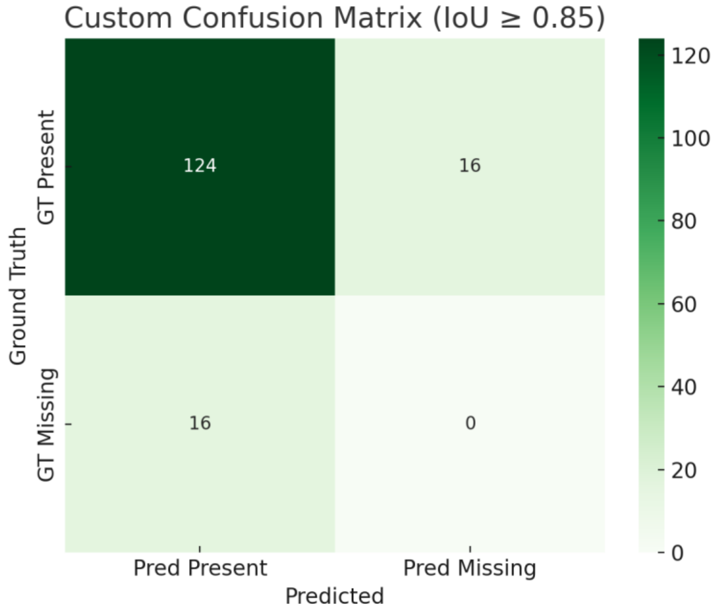
SAMPLE OUTPUT:



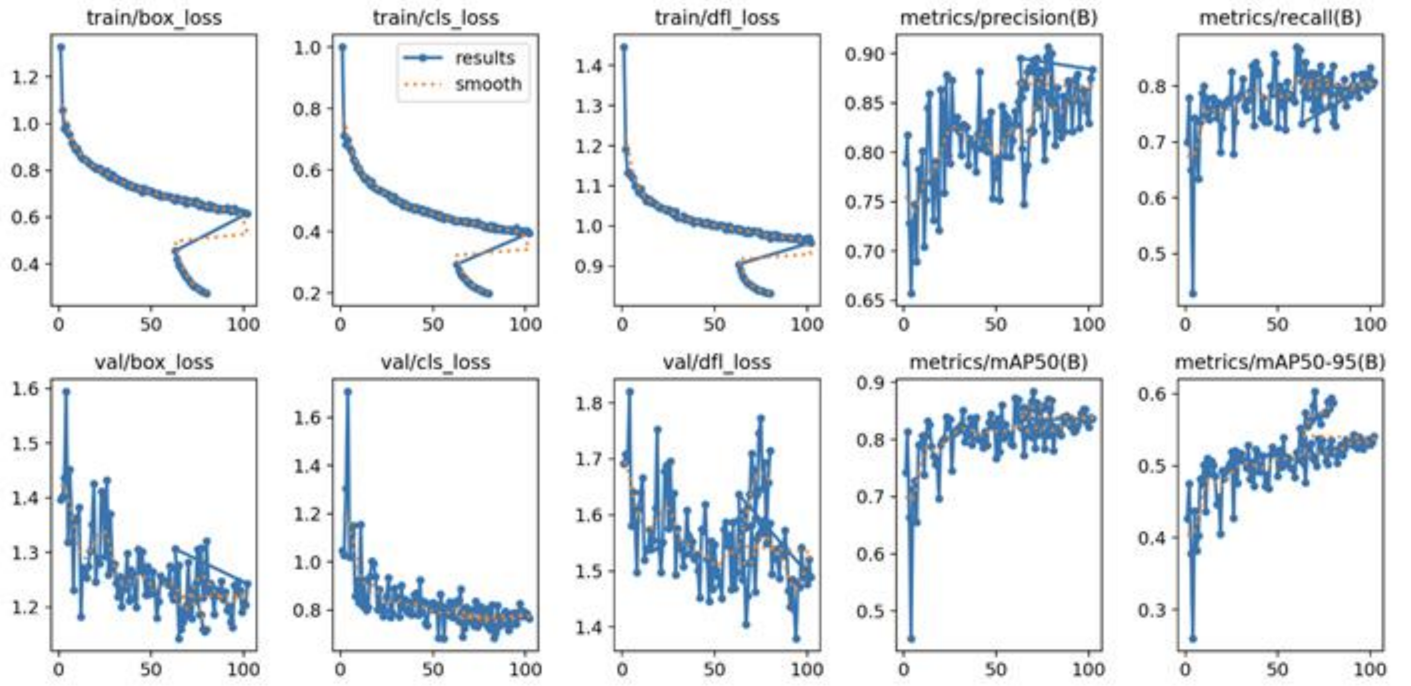
Obb training: vl

<u>Software/package used:</u> Roboflow 3.0 API [Yolov8-based]

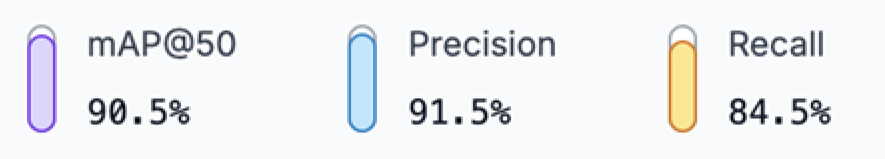
<u>Hardware</u>: On Google Colab T4 GPU 24GB RAM



F1 Score: 0.8857



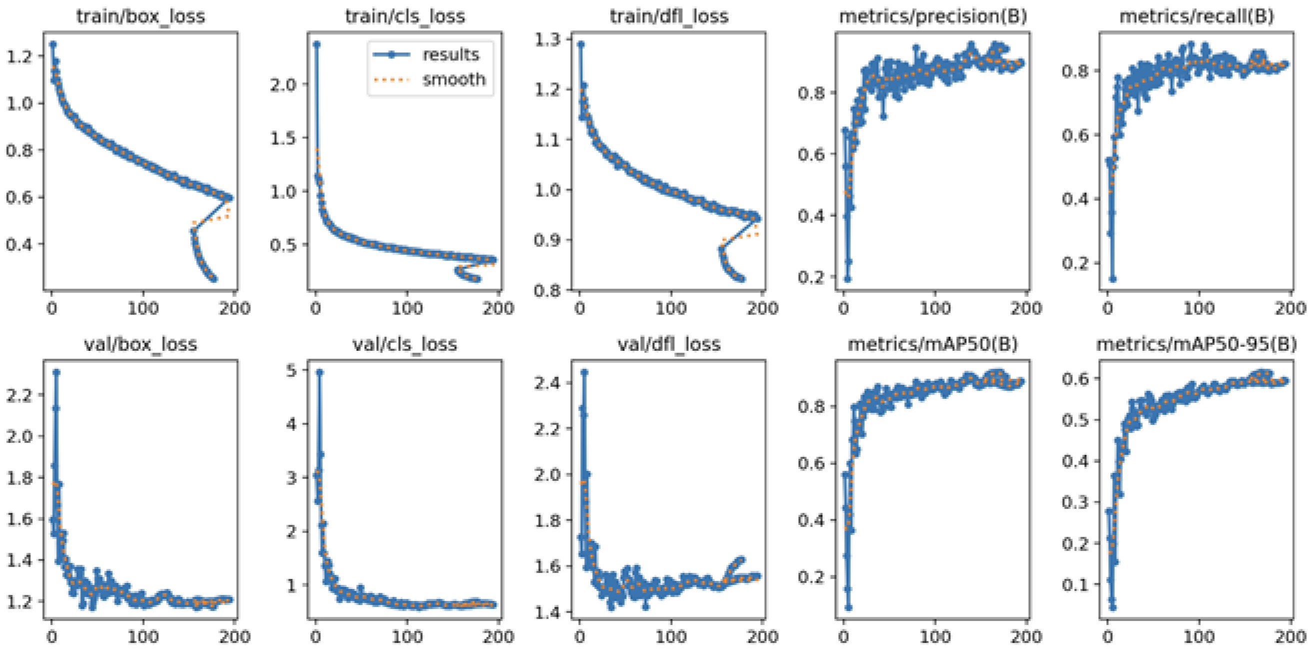
$$\mathrm{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



Obb training: v2

Software/package used: Yolo v11 Roboflow

Hardware: On Google Colab T4 GPU 24GB RAM



mAP@50	Precision	Recall
90.6%	93.0%	82.9%

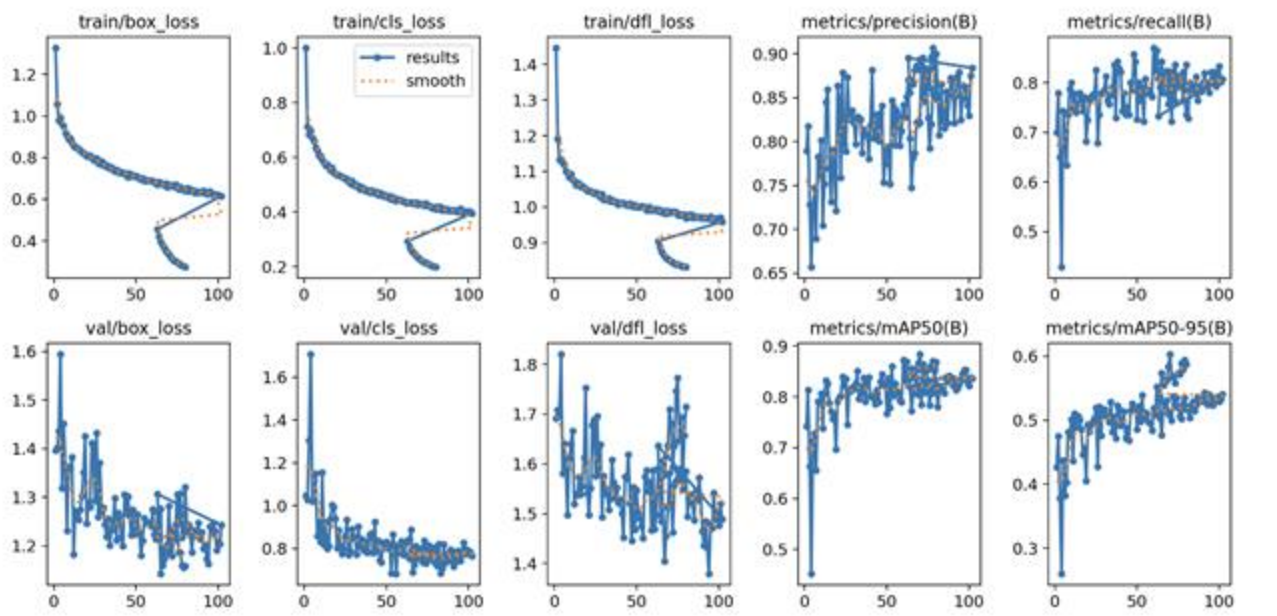
Obb training: v3

Software/package used: Yolo v11 Roboflow

Augmentation: Tilting 25 degrees clock/anticlock-wise

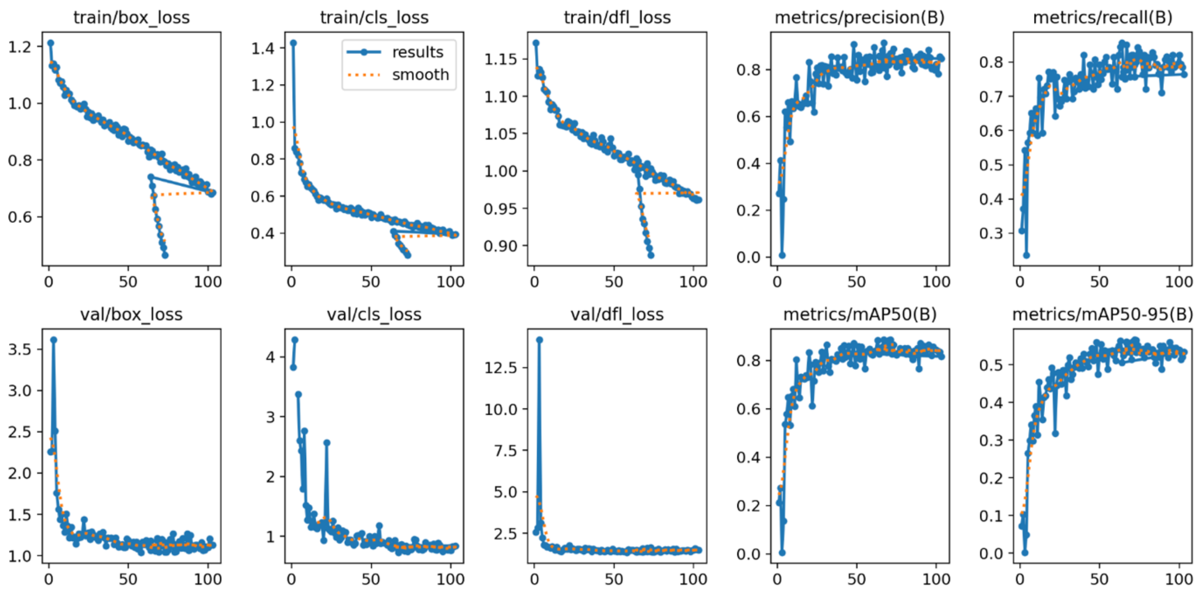
Auto-tilting

Hardware: On Google Colab T4 GPU 24GB RAM



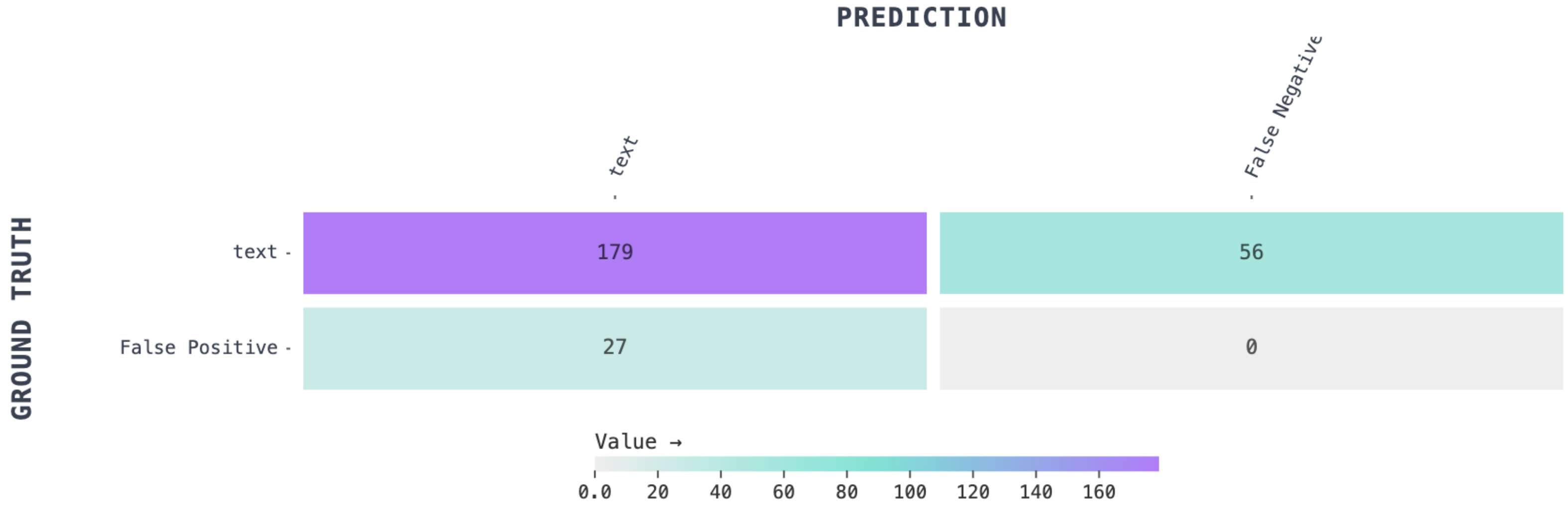
mAP@50	Precision	Recall
87.6%	86.1%	83.8%

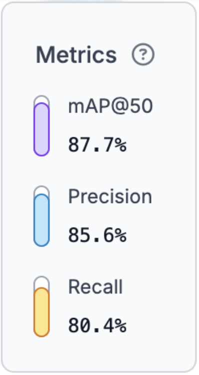
Obb training: v4



Software/package used: **Roboflow (accurate)**

Hardware: On Google Colab T4 GPU 24GB RAM



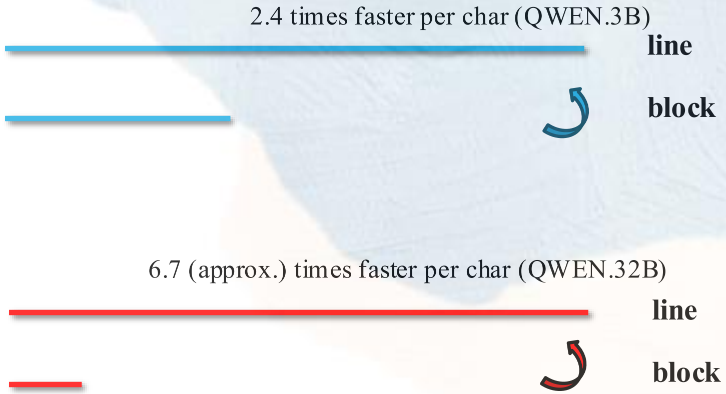


STAGEII. Qwen:

an omnipotent OCR that extracts texts

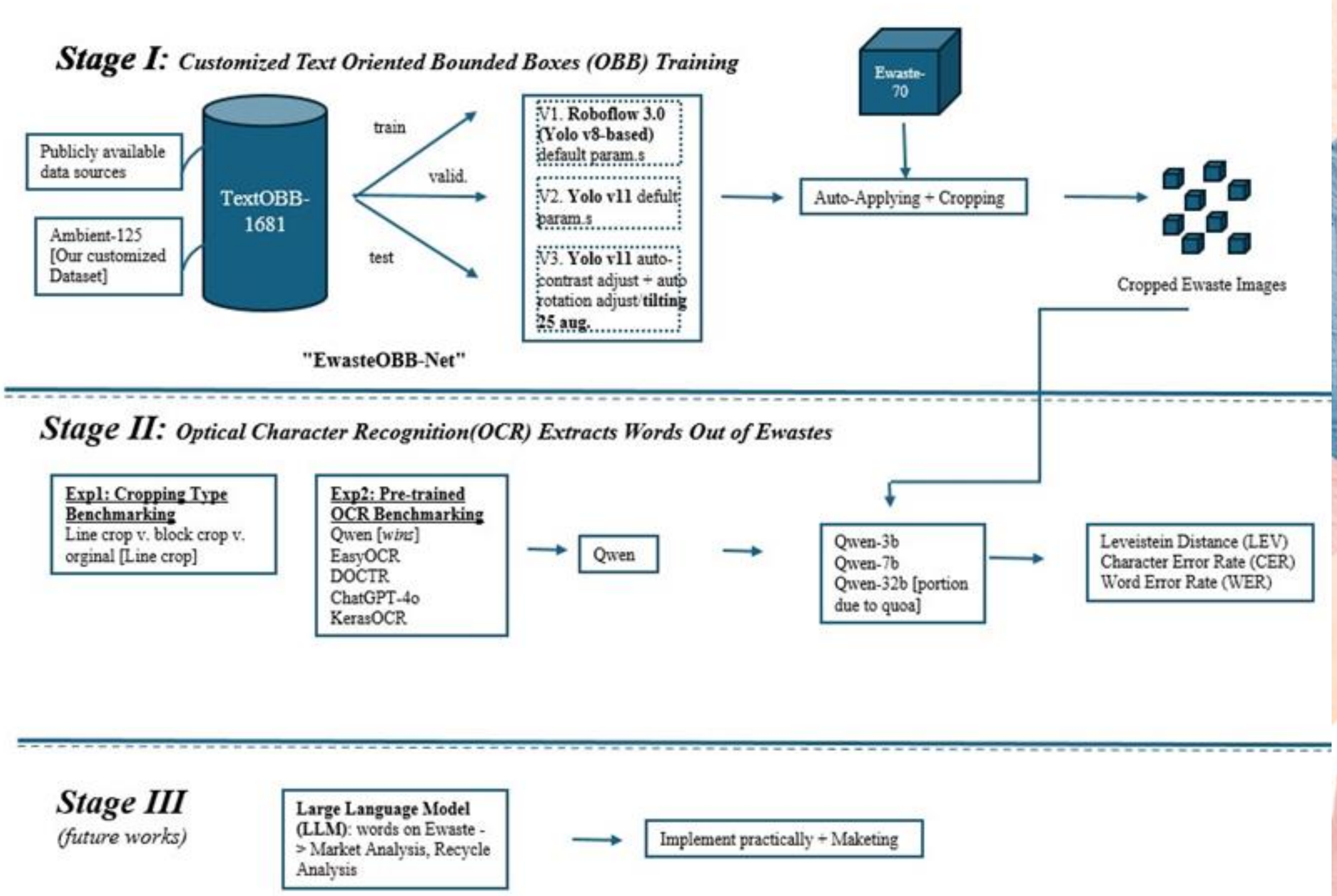
SAMPLE OUTPUT:

Expl: Line v. Block Crop



Exp2: OCR Benchmark

	EasyOCR	GPT-4o	Qwen	DOCTR	Keras-ocr
WER	0.853	0.32	0.03	1.30	0.40
CER	0.5646	0.38	0.13	0.71	0.65
Lev	39.6	28.54	8.18	51.1	58.1


Stage I: Customized Text Oriented Bounded Boxes (OBB) Training
Publicly available data sources
Ambient-125 [Our customized Dataset]
TextOBB-1681
"EwasteOBB-Net"
train
valid.
test
V1. Roboflow 3.0 (Yolo v8-based) default param.s
V2. Yolo v11 defult param.s
V3. Yolo v11 auto-contrast adjust + auto rotation adjust/tilting 25 aug.
Ewaste-70
Auto-Applying + Cropping
Cropped Ewaste Images
Stage II: Optical Character Recognition(OCR) Extracts Words Out of Ewastes
Exp1: Cropping Type Benchmarking
Line crop v. block crop v. orginal [Line crop]
Exp2: Pre-trained OCR Benchmarking
Qwen [wins]
EasyOCR
DOCTR
ChatGPT-4o
KerasOCR
Qwen
Qwen-3b
Qwen-7b
Qwen-32b [portion due to quoa]
Leveistein Distance (LEV)
Character Error Rate (CER)
Word Error Rate (WER)
Stage III
(future works)
Large Language Model (LLM): words on Ewaste -> Market Analysis, Recycle Analysis
Implement practically + Maketing

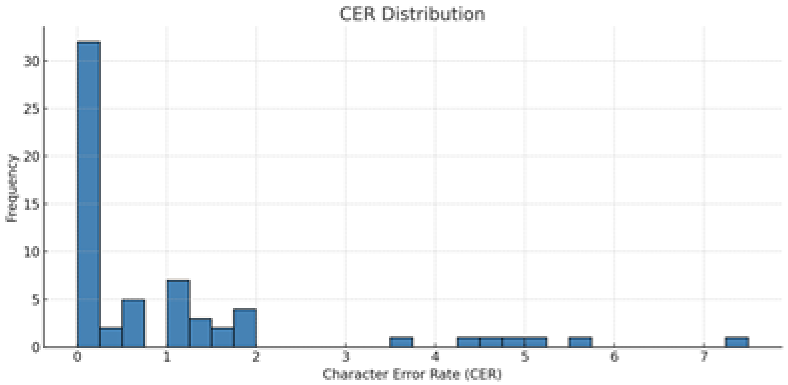
What does our Ewaste-Net produce?

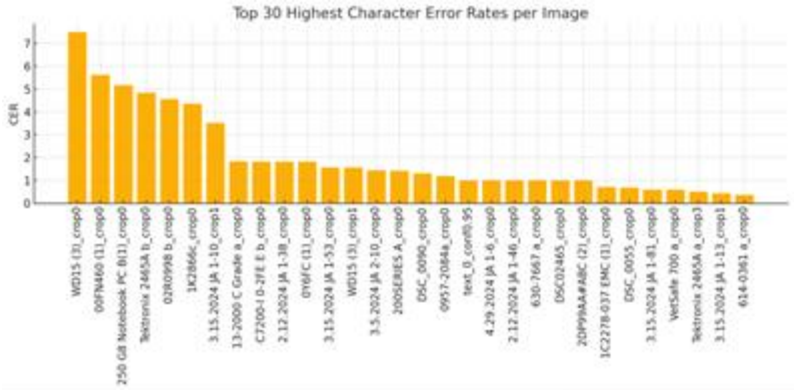
RESULTS

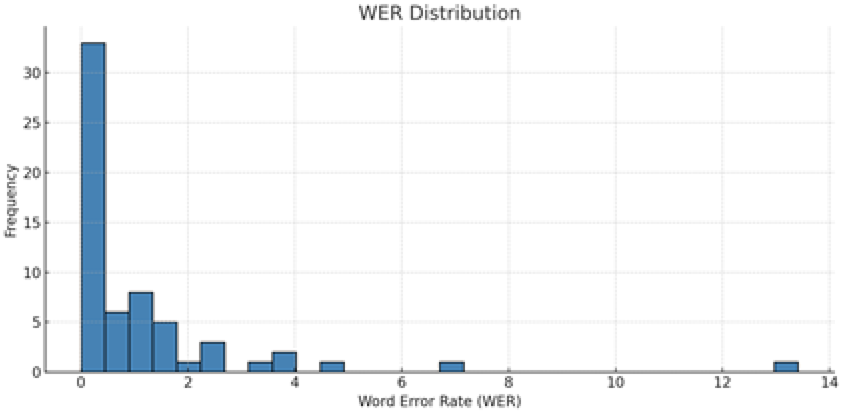
Avg. CER: **0.9890**

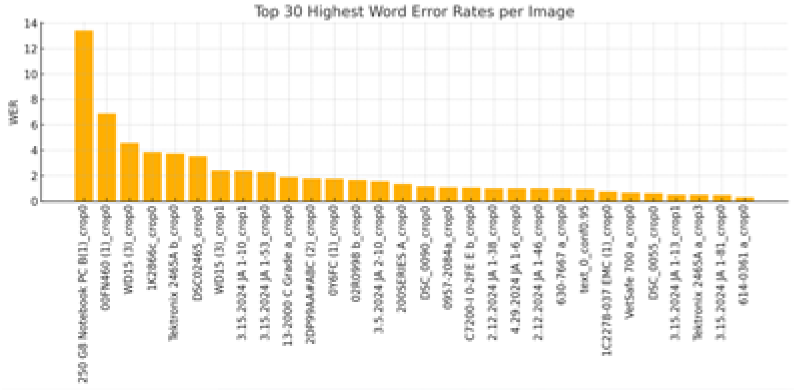
Avg. WER: **1.0538**

Result Visualization









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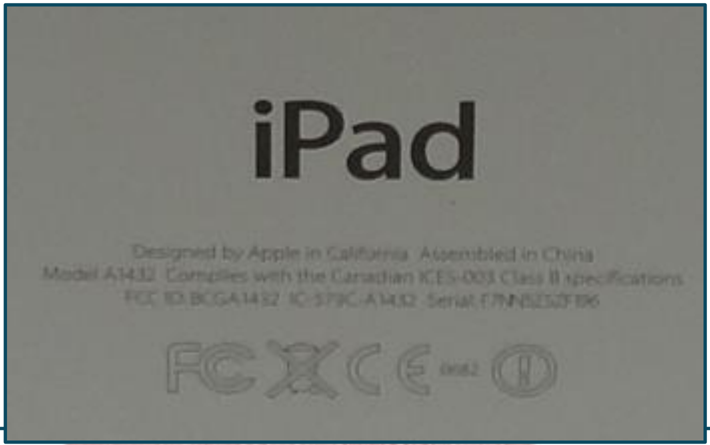
hp
OfficeJet 200 Mobile Printer
On-the-go business printing
Easily print from your smartphone or tablet
Imprimez facilement à partir de votre téléphone intelligent ou de votre tablette


iPad
Designed by Apple in California Assembled in China
Model A1432 Complies with the Canadian ICES-003 Class B specifications

Stage III:
LLMs for E-Waste Understanding

Future Anticipation

Goal:
Transform raw OCR text into structured, meaningful product data using Large Language Models (LLMs).

Key Capabilities:

- Interpret messy or partial text.
- Extract relevant product fields.
- Provide context-aware summaries.
- Estimate resale or recycling potential.

Why LLMs?
LLMs understand *context* and *semantics*, enabling more human-like reasoning over noisy or inconsistent data.

Typical Input & Output Flow

Input: "HP Pavilion dv6, S/N: CNF1234XYZ, Prod Date: 2012/07"

LLM Process:

Tokenization → Named Entity Recognition → Text normalization & completion → Field mapping & validation

Output:

Field	Value
Brand	HP
Model	Pavilion dv6
Serial Number	CNF1234XYZ
Production Date	July 2012
Category	Laptop

Key Extraction Targets

Entities LLMs Extract from Text:

- **Brand** – Manufacturer name
- **Model** – Full device model/series
- **Serial Number** – Unique identifier
- **Production Date** – Year and month of manufacture
- **Product Category** – Phone, Laptop, Router, etc.
- **Special Tags** – “Refurbished”, “Battery Inside”, etc.

Purpose: Enables downstream modules to lookup databases or rules for price/recycling.

Estimating Resale and Recyclability

- Given the collected and polished metadata, we can easily build a model to predict the resale price and recyclability of the e-waste product.

- After this, we finished an end-to-end e-waste sorting and marketing model based on merely the images as input.👏

Underestimation-

huge potentials ahead

FUTURE WORKS & DRAWBACKS

1. Stage I upgrade: Automatic line croping algorithm can be easily trained given *sufficient and standardized* Ewaste factory images. This will save both time and space complexity for Stage II,III

2. Qwen upgrade: Qwen has three main versions, 3b, 7b, and 32b, and a charged 72b. An upgrade of GPU, RAM, SSD with *Linux Cluster* would enable to access at least Qwen.7b, which will boost both accuracy and time complexity.

3. Underestimation: Ground Truth table is provided by us bare eyes, if it can produce *real ground truth* (independent of eyesights) would produce a much objective meaningful benchmark index.

Special Thanks

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Mr. Jerome Barczykowski