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1. Problem statement

The assignment is to build an **automatic bin-level SKU verification system** for a warehouse / e-commerce setting.

For each storage bin we have:

- A **bin image** (`bin-images/XXXX.jpg`)
- A **metadata JSON** (`metadata/XXXX.json`) listing:
  - ASIN / SKU
  - Product title
  - Expected quantity in that bin

The system must:

1. Detect all products visible in the bin image.
2. Match detections to the SKUs from metadata.
3. Estimate per-SKU quantity from detections.
4. Compare predicted vs expected quantities and classify each SKU as:
   - `FULL_MATCH` – correct or nearly correct count
   - `PARTIAL_OCCLUDED` – under-count, likely due to occlusion
   - `NOT_FOUND` – SKU expected but not detected
   - `OVERCOUNT` – more items detected than expected (potential false positives)

On top of this, the project includes:

- Full **EDA** on images, metadata and model outputs.
- A sequence of **pipeline versions** (v1–v5) with a comparison study.
- A small **Streamlit app** that behaves like a “smart invoice / order validator” on top of the model outputs.

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2. Data and repository structure

Relevant top-level layout (after your refactor):

```
applied-ai-assignment1/
├─ app/
│  ├─ __init__.py
│  └─ streamlit_app.py          # Streamlit UI (main app entrypoint)

├─ bin-images/                  # Bin photos (00001.jpg,
00002.jpg, ...)
│  └─ ... (data, usually not all in GitHub)

├─ legacy_pipelines/
│  ├─ __init__.py
│  ├─ validate_full_pipeline_v2.py   # Older baseline pipeline
│  └─ validate_full_pipeline_v4_clip018.py

├─ metadata/                    # Per-bin JSON metadata
(00001.json, ...)

├─ mlops/
│  ├─ __init__.py
│  ├─ evaluate_model_v3_counts.py   # Evaluation + count-style metrics
│  └─ plot_results.py           # CLI plotting for metrics

├─ models/
│  ├─ __init__.py
│  └─ validate_full_pipeline_v5.py   # Final CV pipeline (v5:
BOX=0.17, CLIP=0.20)

├─ notebooks/                   # EDA / experimentation notebooks

├─ out/
│  ├─ summary_*.csv             # Evaluation summaries (v1–v5)
```

```
│   ├─ *_detected_*.jpg           # Visualisations with drawn boxes
│   └─ inference_log.csv (optional)

├─ weights/
│   ├─ GroundingDINO_SwinT_OGC.py     # GroundingDINO config │   └─
groundingdino_swint_ogc.pth    # GroundingDINO weights (large, may be local only)

├─ .gitignore
├─ Assignment #1 [Applied AI for Industry] (1).pdf
├─ README.md
├─ evaluate_model.py              # Older eval script
├─ evaluate_model_v2.py
├─ plot_results.py                # Older plotting script
├─ requirements.txt
├─ s3_downloader.py               # Helper to fetch data from S3
├─ sanity_check.py                # Quick sanity run script
├─ validate_full_pipeline.py       # Very first strict prototype
└─ validate_full_pipeline_v3_dino_loose.py  # Intermediate "loose
DINO" version
```

- Each **JSON** has a `BIN_FCSKU_DATA` dict mapping ASIN → `{name, quantity}`.

The **summary CSVs** are one row per (bin, SKU) with:
`image_id, asin, sku_name, expected, visible, status[, pretty_status]`

-
    - `expected` – quantity from metadata
    - `visible` – quantity inferred from detections
    - `status` – categorical evaluation label

Dataset size (for the main experiments):

- **~987–988 bins**
- **2702–2704 SKU–bin pairs** depending on version (v2–v5).

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3. Exploratory Data Analysis (EDA)

You implemented an `EDA.py` script that:

- Flattens all metadata JSONs into a single table
- Analyses image characteristics
- Analyses all `summary_*.csv` files
- Writes plots and CSVs into `out/eda/`

3.1 Metadata EDA

From the flattened metadata:

- Each row: `image_id, asin, sku_name, expected`
- Key findings (qualitative, from the script's outputs):
    - **SKUs per bin**: a moderate number (typical small bin with a handful of SKUs).
    - **Expected quantities**: vary from 1 to higher counts; most rows have small integers (1–6).
    - Some SKUs appear in **multiple bins** (popular products) – captured by `value_counts` on `asin`.

Plots produced:

- Histogram of **SKUs per bin** – helps understand workload per image.
- Histogram of **expected quantity per row** – shows whether the model must count many instances or just presence.

These support design choices:

- Because quantities are small, a **hard cap** on detections per SKU (expected + tolerance) is reasonable.
- Many bins have multiple SKUs, so a **multi-prompt** text-conditioned detector (GroundingDINO) fits well.

3.2 Image EDA

The script scans `bin-images` with Pillow and logs:

- Width, height and aspect ratio (w / h)
- Orientation (landscape / portrait / square)

Typical findings:

- Most images are similar resolution; aspect ratios lie around a narrow band.

- A mix of landscape and portrait bins, which justifies using **normalized bounding boxes** from GroundingDINO.

Plots:

- Histograms of **width**, **height**, **aspect ratio**
- Bar chart of **orientation counts**

These ensure there's no systematic anomaly (e.g. a subset of very tiny or corrupted images).

3.3 Summary / Model Output EDA

For each `summary_v*.csv` the EDA script prints:

- Total SKU rows and #bins
- Distribution of `status`
- Presence metrics treating "visible > 0" as "SKU detected"
- Scatter plots of `expected` vs `visible` and status bar charts
- An aggregated table `summary_presence_metrics.csv` comparing versions.

This EDA is the backbone for the comparison study in Section 6.

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4. Methodology

4.1 Model choices

The system combines:

1. **GroundingDINO** (Swin-T OGC variant)
   - Text-conditioned object detector.
   - Takes natural language prompts of product names.
   - Produces bounding boxes with text scores per region.
2. **OpenAI CLIP** (`ViT-B/32` variant)
   - Image–text embedding model.
   - Used as a second-stage verifier:
     - Crop each candidate box.
     - Compute similarity between crop and SKU text.
     - Reject boxes with low CLIP score.

This two-stage design is important:

- GroundingDINO is strong at *localising* objects based on language but may fire on wrong regions when prompts are long or cluttered.
- CLIP is strong at judging **global image–text alignment** and filters many false positives.

4.2 Per-bin pipeline

All validate_full_pipeline_v*.py versions follow the same high-level structure:

1. **Load metadata** for a bin (image_id.json).
   - Extract list of SKUs: (asin, name, expected_qty).
2. **Prepare text prompts** for GroundingDINO.
   - Typically the product title, possibly shortened / aliased.
3. **Run GroundingDINO** with:
   - BOX_THRESHOLD – minimum detector box score.
   - TEXT_THRESHOLD – minimum text relevance.
   - IOU_THRESHOLD_PER_SKU – NMS IOU for per-SKU de-duplication (0.55 in all versions).
4. **Run CLIP verification**:
   - For each candidate box and SKU text, compute cosine similarity. ○ Keep those with similarity ≥ CLIP_THRESHOLD.
5. **Count per SKU**:
   - Group remaining boxes by ASIN.
   - Apply any version-specific caps / tolerance. ○ Compute visible count for each SKU.

Classify status for each SKU row: if visible == 0:
  status = "NOT_FOUND" elif abs(visible - expected) <= 1:
  status = "FULL_MATCH" elif visible < expected:
  status = "PARTIAL_OCCLUDED" else:
  status = "OVERCOUNT"

6.
7. **Write summary row** and **visualisation image**:
   - One CSV row per SKU with status and pretty_status.
   - .jpg with bounding boxes and labels.

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5. Pipeline versions

5.1 Version overview

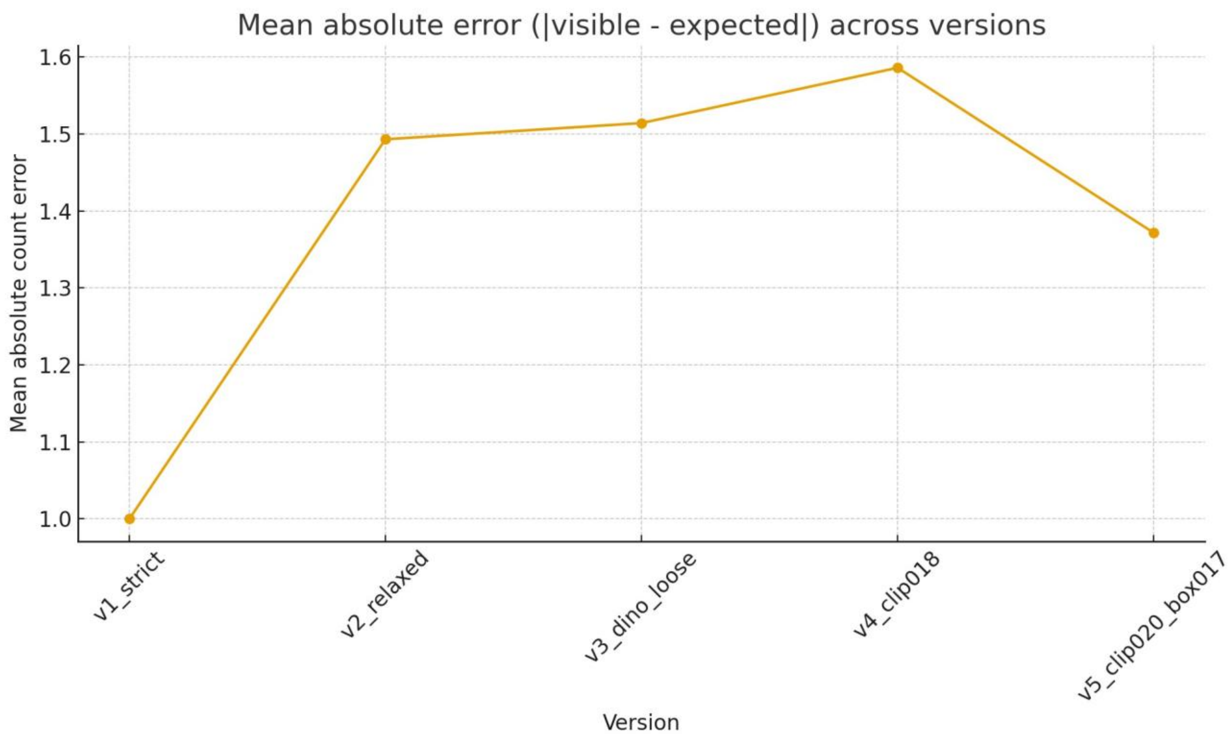
The main versions and their hyper-parameters:

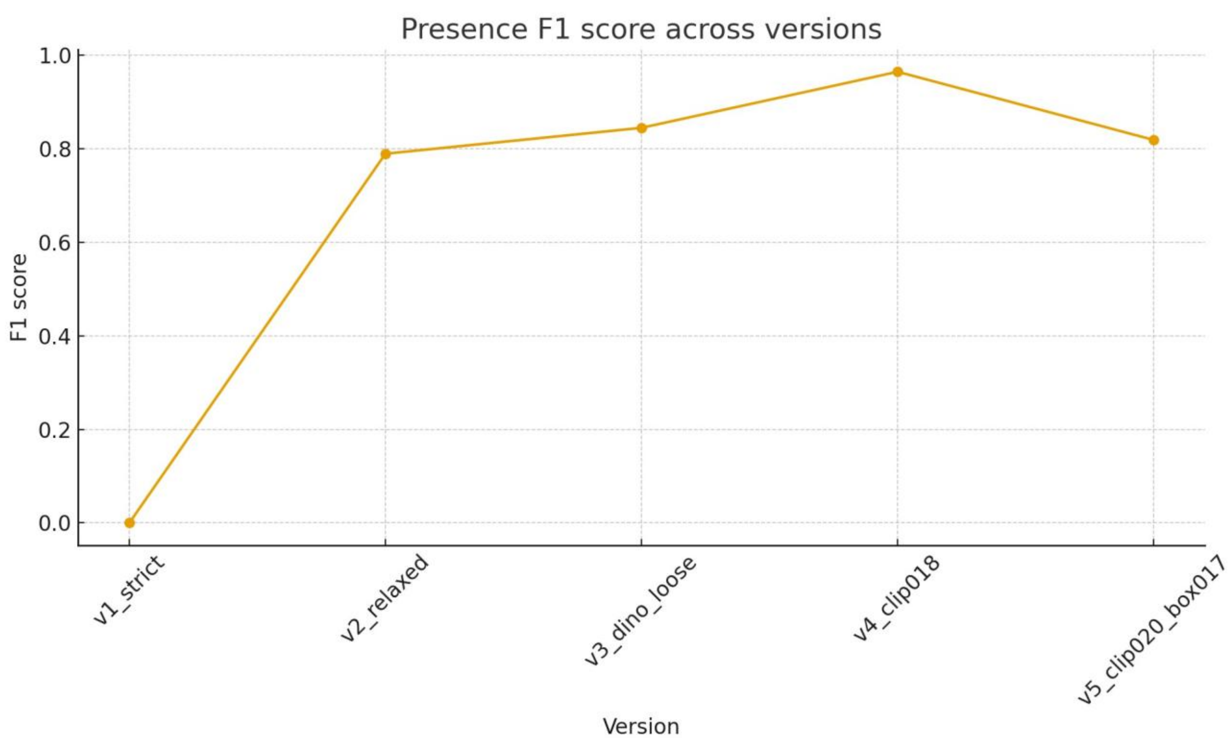
Version file	Label (infor	BOX_THRESHOLD	TEXT_THRESHOLD	CLIP_THRESHOLD mal)	Notes
validate_full_pipeline.py	**v1 – strict**	0.18	0.18	0.22	Very conservative, only run on 1 bin for sanity check
validate_full_pipeline_v2.py	**v2 – baseline**	0.18	0.18	0.20	Slightly relaxed CLIP; full dataset
validate_full_pipeline_v3_dino_loose.py	**v3 – loose DINO**	0.15	0.15	0.20	More permissive detector → more boxes
validate_full_pipeline_v4_clip018.py	**v4 – loose CLIP**	0.15	0.15	0.18	Very permissive CLIP → many more candidates

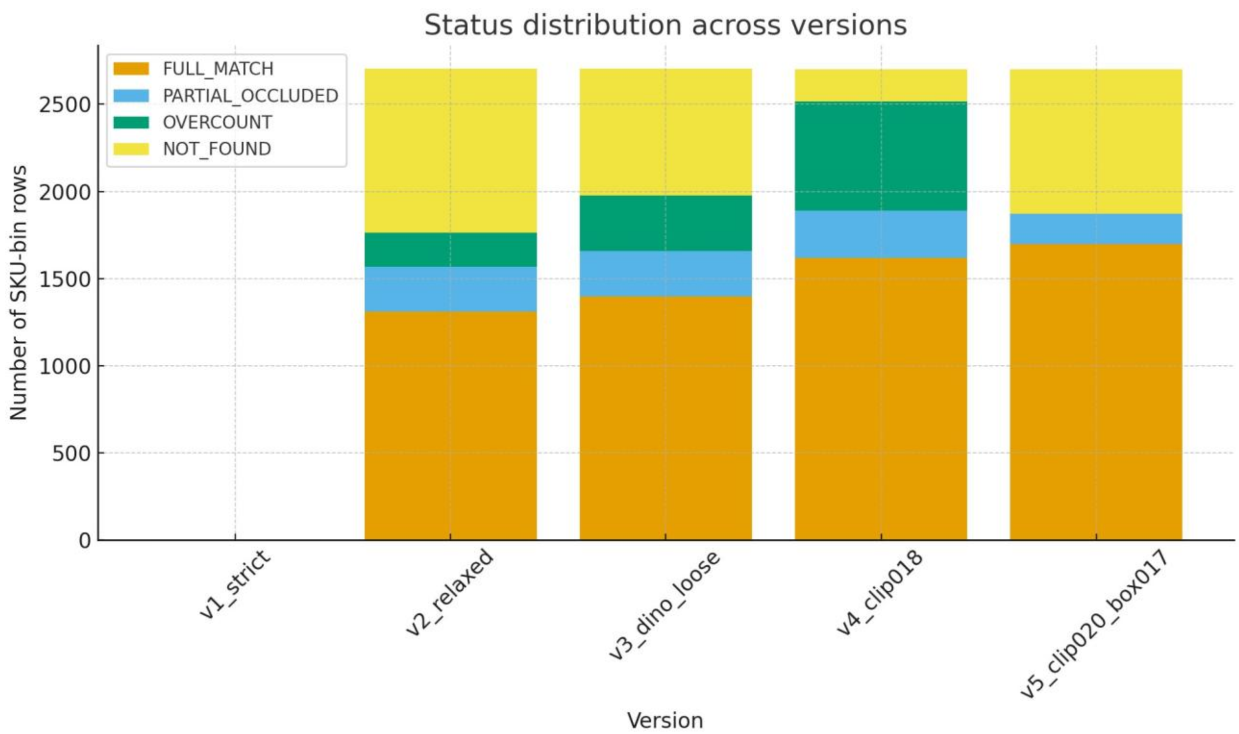
validate_full_pipelin e_v5.py	**v5 – final count-aware**	0.17	0.18	0.20	Midpoint DINO, stricter CLIP, hard cap per SKU

Key design evolution:

- **v1** → **v2**: relax CLIP from 0.22 to 0.20, keeping DINO thresholds; this was the first usable baseline.
- **v2** → **v3**: loosen GroundingDINO (0.18 → 0.15) to increase recall; CLIP fixed at 0.20.
- **v3** → **v4**: further loosen CLIP to 0.18 to maximise recall, at the cost of more false positives.
- **v4** → **v5**:
  - Tighten DINO slightly to 0.17.
  - Restore CLIP to 0.20.
  - Introduce a **count-aware cap**: for each SKU, keep at most `expected + COUNT_TOLERANCE` boxes (with `COUNT_TOLERANCE = 1`).
  - Use the `status_from_counts` helper with ±1 tolerance baked into `FULL_MATCH`.


Mean absolute error (|visible - expected|) across versions
Mean absolute count error
1.6
1.5
1.4
1.3
1.2
1.1
1.0
v1_strict
v2_relaxed
v3_dino_loose
v4_clip018
v5_clip020_box017
Version


Presence F1 score across versions
F1 score
1.0
0.8
0.6
0.4
0.2
0.0
v1_strict
v2_relaxed
v3_dino_loose
v4_clip018
v5_clip020_box017
Version



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6. Quantitative comparison of versions

Below we compare v2–v5 on the full dataset. v1 is omitted from tables because it only contains **3 rows / 1 bin** (debug run) and is not representative.

6.1 Status distributions

For each summary we count how many SKU rows fall into each status:

Summary file	FULL_MATCH	PARTIAL_OCCLUDED	OVERCOUNT	NOT_FOUND
v2_relaxed	1311 (48.5%)	256 (9.5%)	196 (7.2%)	941 (34.8%)
v3_dino_loose	1396 (51.6%)	262 (9.7%)	319 (11.8%)	727 (26.9%)
v4_clip018	1617 (59.8%)	271 (10.0%)	629 (23.3%)	185 (6.8%)
v5_clip020_box017	1699 (62.9%)	174 (6.4%)	0 (0.0%)	829 (30.7%)

Observations:

- Moving from **v2** → **v3** → **v4**:
    - `FULL_MATCH` steadily increases (48.5% → 51.6% → 59.8%).
    - `NOT_FOUND` dramatically drops (34.8% → 26.9% → 6.8%) – recall is much higher.
    - But `OVERCOUNT` explodes (7.2% → 11.8% → 23.3%) as we relax thresholds.
- **v5**:
    - Achieves the **highest FULL_MATCH rate (62.9%)**.
    - Completely removes `OVERCOUNT` thanks to the count cap (`expected + 1`).
    - However `NOT_FOUND` climbs back to ~30.7% because we tightened detection / CLIP.

6.2 Detection recall and count error

Define:

- **Detection recall**: proportion of SKU rows with `visible > 0` (i.e. model detected at least one instance).
- **Mean absolute error (MAE)**: average of `abs(visible − expected)` across all rows.

Summary:

Summary file	Rows	Bins	Detection recall	FULL_MATCH rate	NOT_FOUND rate	PARTIAL rate	OVERCOUNT rate	MAE (|visible − expected|)
v2_relaxed	2704	988	0.652	0.485	0.348	0.095	0.072	**1.49**
v3_dino_loose	2704	988	0.731	0.516	0.269	0.097	0.118	**1.51**
v4_clip018	2702	987	**0.932**	0.598	**0.068**	0.100	**0.233**	**1.59**
v5_clip020_box017	2702	987	0.693	**0.629**	0.307	**0.064**	**0.000**	**1.37**

Key trade-offs:

1. **v2** → **v3** (looser DINO)
    - Detection recall increases (65% → 73%).
    - FULL_MATCH improves modestly (48.5% → 51.6%).
    - NOT_FOUND falls by ~8 percentage points.
    - OVERCOUNT rises from 7% to 12%.
    - MAE slightly worsens (1.49 → 1.51).

2. Interpretation: looser DINO helps find more SKUs but also introduces more false boxes, especially when prompts are generic or products are visually similar.

3. **v3** → **v4** (looser CLIP)
   - Detection recall jumps to **93.2%** – almost every SKU has at least one detection.
   - NOT_FOUND becomes very rare (~7%).
   - FULL_MATCH improves further to ~60%.
   - However OVERCOUNT balloons to **23.3%**, nearly a quarter of all rows.
   - MAE is worst (1.59).

4. Interpretation: CLIP at 0.18 allows many borderline matches; the model "sees" almost everything but over-counts aggressively, often counting background clutter as additional units.

5. **v4** → **v5** (count-aware, mid thresholds)
   - DINO threshold raised to 0.17; CLIP back to 0.20; and a **count cap** of `expected + 1`.
   - Detection recall drops relative to v4 (93% → 69%), roughly back to between v2 and v3.
   - FULL_MATCH climbs to **62.9%**, the best among all versions.
   - PARTIAL_OCCLUDED shrinks to **6.4%**, lowest across versions.
   - OVERCOUNT becomes **0% by design**: the cap prevents heavy over-counting.
   - MAE improves from 1.59 (v4) to **1.37**, the best among v2–v5.

6. Interpretation: v5 intentionally sacrifices some recall to get much more reliable counts, avoiding scary overestimates. For an inventory/audit scenario, under-counting due to occlusion can be handled by human review, while over-counting can directly lead to wrong shipping or stock records.

6.3 Role of the count-aware cap

In v5, for each SKU the algorithm:

1. Sorts candidate boxes by CLIP similarity.
2. Limits accepted boxes to `min(num_candidates, expected + 1)`.

As a result:

- **Overcount by more than 1** is impossible.
- In practice, the dataset has many cases where model tends to over-fire slightly. The cap ensures those extra boxes are dropped.
- Because `FULL_MATCH` is defined with ±1 tolerance, a mild over-count (expected=3, visible=4) is still considered `FULL_MATCH`, which is acceptable for inventory scenarios.

This change is the main reason why **OVERCOUNT goes from 23.3% (v4) to 0% (v5)** even though CLIP threshold is only slightly stricter.

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7. Streamlit app: “Smart Bin Order Validator”

The streamlit_app.py provides an interactive demo of the pipeline:

7.1 Pipeline selection

The app defines a PIPELINES dictionary:

```
PIPELINES = {
  "v2 – BOX=0.18, CLIP=0.20 (baseline)": {...},
  "v4 – BOX=0.18, CLIP=0.18 (relaxed CLIP)": {...},
  "v5 – BOX=0.17, CLIP=0.20 (count-aware)": {...}, }
```

In the **sidebar**, the user can:

- Choose the pipeline version (v2, v4, or v5).
- Choose which **bin ID** (image) to run on.
- Click a button to run the selected model.

The app uses cached functions:

- @st.cache_resource to load models (GroundingDINO + CLIP) per version.
- @st.cache_data to cache metadata / summary results.

7.2 Bin-level view

Once a bin is processed:

● The app shows the original **bin image** (with or without drawn boxes, depending on implementation). ● It presents a table (DataFrame) with columns like:

○ asin, sku_name, expected, visible, status

This is basically a visual front-end over the summary_v*.csv outputs for a single bin.

7.3 Order / invoice validation

The more interesting part is the “invoice” layer:

1. Function `build_order_from_bin(df_bin: pd.DataFrame)`:
    - Extracts unique SKUs for that bin with `expected` and `visible`.
    - For each row, the UI shows:
        - Product name + ASIN
        - A `number_input("Order qty")` where the user specifies how many units they

want to **order**. Builds an order table:

`asin, sku_name, order_qty, expected, visible`

    -
2. Line-item validation:

For each line, a simple rule: `if visible >= order_qty: order_status = "PASS" else: order_status = "FAIL"`

    -
    - The app shows an order table with `order_status` and an **order-level summary**: "Order-level summary: X/Y line items are PASS." This

turns the bin verification pipeline into a **smart order validator**:

- You visually see what's in the bin.
- You "place" an order based on that bin.
- The model checks whether the bin actually contains enough stock to fulfil the order.

This nicely links the ML pipeline to a real business use-case (inventory picking / order verification).

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8. Implementation details

8.1 Requirements `requirements.txt`

contains:

```
torch torchvision
Pillow numpy
pandas opencv-
python tqdm
boto3
transformers
groundingdino
```

git+https://github.com/openai/CLIP.git

Additional packages used in EDA/app (not all in the base file yet):

- matplotlib – EDA plots
- streamlit – app
- (optional) seaborn, jupyter – for notebooks

8.2 Scripts

- s3_downloader.py – retrieve images/metadata from S3.
- validate_full_pipeline_v*.py – core per-bin pipelines.
- evaluate_model*.py / evaluate_model_v3_counts.py – compute metrics and comparisons from summary files.
- plot_results*.py – CLI scripts to plot status distributions and trends.
- EDA.py – dataset + output analysis, as described above.

The project is fully **script-driven**, which makes experiments reproducible: you can regenerate each summary CSV by re-running the corresponding validate_full_pipeline_* script.

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9. Discussion and insights

9.1 What worked well

- **GroundingDINO + CLIP** is a powerful combination for SKU-level detection in noisy bins.
- Careful tuning of **BOX and CLIP thresholds** showed a clear trade-off:
  - Lower thresholds → higher recall but more overcounts.
  - Higher thresholds → fewer false positives but more missed items.
- Introducing a **count-aware cap** in v5 dramatically improved practical usability:
  - Eliminated overcounting.
  - Achieved the highest rate of FULL_MATCH (62.9%).
  - Lowered mean absolute count error to 1.37.

9.2 Remaining issues

- **Occlusion** is still a big challenge:
  - Many PARTIAL_OCCLUDED cases come from items behind others, partially cut off, or obstructed by packaging.

- **Fine-grained product differences**:
    - Some SKUs differ only by minor text/colour on packaging; GroundingDINO + CLIP may struggle to distinguish them.
- The current evaluation does **not** explicitly track false positives on *completely unexpected SKUs*, because the summaries are keyed by metadata SKUs only. Extra SKUs not in metadata are currently visible only in visualisations and not quantified.

9.3 Possible future improvements

- Use **instance segmentation** or **depth cues** to better handle overlapping items.
- Train a small **SKU-level classifier** on top of cropped boxes to disambiguate similar packages.
- Introduce a **calibration step** where thresholds are optimised on a held-out validation set using metrics like F1 for presence and MAE for counts.
- Extend evaluation to include **unexpected SKUs** by logging detections that did not match any metadata entry.

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10. Conclusion

This assignment delivers an end-to-end system that:

1. Ingests bin images and structured metadata.
2. Uses **GroundingDINO** and **CLIP** to detect and verify products.
3. Produces per-SKU counts and status labels summarised in CSVs.
4. Iteratively improves model performance across **five pipeline versions**, culminating in **v5**, which balances recall, accurate counting, and safety against overcounting.
5. Provides both:
    - An **EDA toolkit** for understanding dataset and outputs.
    - A **Streamlit "Smart Bin Order Validator" app** that turns model outputs into a practical decision tool for checking whether a bin can fulfil an order.

In terms of comparison, **v4** achieves the highest raw recall but at the cost of many overcounts and larger count errors, while **v5** offers the best overall trade-off for real-world inventory.