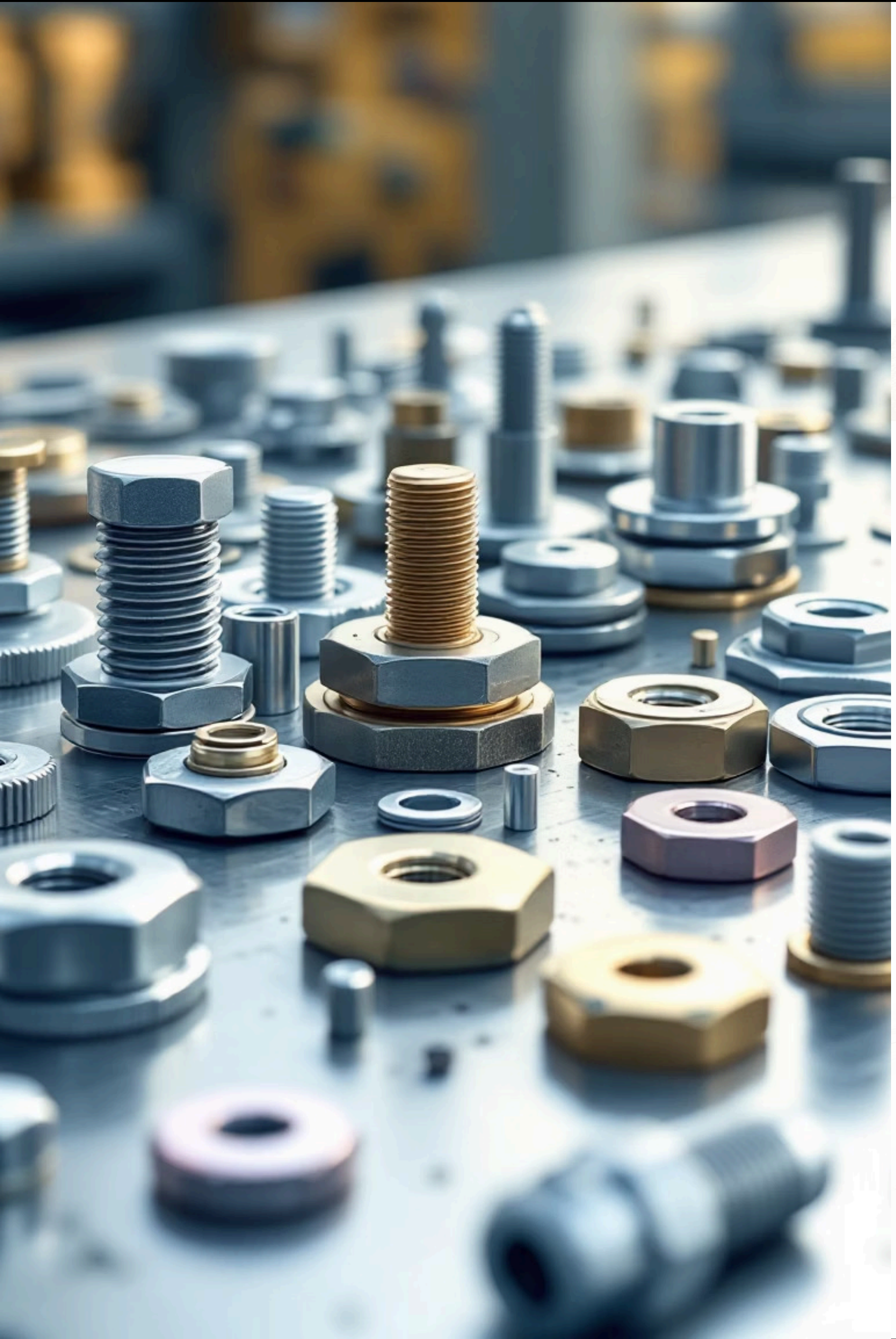

# Solidworks AI Hackathon

## Precision Counting of Industrial Parts via YOLOv8 Object Detection

## Achieving 1.000 "Exact Match" Accuracy on Synthetic CAD Data


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# Problem Understanding & Context

**The Task:** Exact counting of 4 mechanical components (Bolt, Nut, Washer, Locating Pin) in synthetic CAD environments.

## The "Zero-Error" Constraint:

- **Evaluation Metric:** Exact Match Accuracy.
- **Condition:** $\mathrm{Score} = 1 \iff \forall c \in Classes : \mathrm{Pred\_}c = \mathrm{True\_}c$
- **Implication:** A single missed washer results in a total failure (0 score) for the image.

## Data Nature:

- **Type:** Synthetic CAD Renderings.
- **Characteristics:** High edge sharpness, consistent lighting, but significant occlusion (washers hidden under bolts).

**Engineering Goal:** Maximize **Precision** (No false positives) and **Recall** (No missed objects) simultaneously to 1.0.

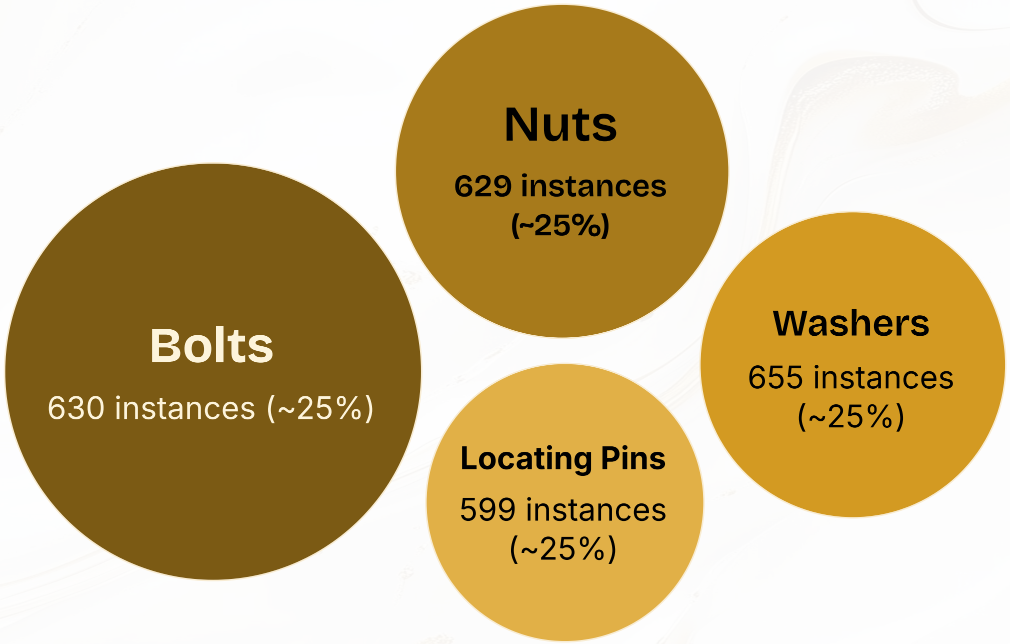
# Dataset Insights & Strategy

### Dataset Audit (100% Supervision):

- **Total Images:** 10,000.
- **Annotated Images:** 10,000 (100%).
- **Empty/Background Images:** 0 (0.00%).

### Class Distribution (Perfectly Balanced):

- **Strategy:** The dataset's natural balance allowed us to use standard Cross-Entropy Loss without needing weighted sampling.
- **Implication:** The model is constantly active; there are no "rest" frames. This requires high robustness against False Positives within active scenes.




**Validation Set Breakdown**

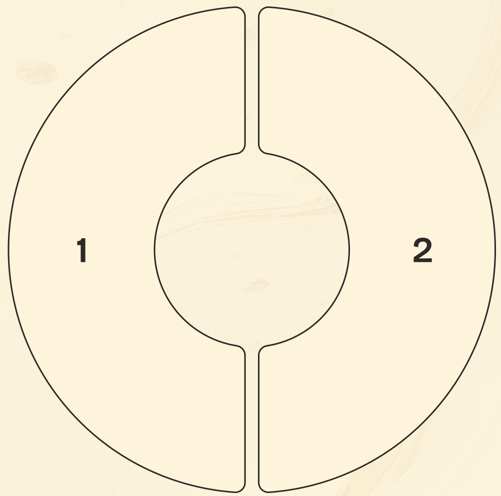
# Model Architecture Selection

## Choice: YOLOv8 Small (yolov8s)

## Why Object Detection > Regression?

- **Regression (Counting CNN):** Outputs a continuous float (e.g., bolts). Rounding errors cause failure in exact-match tasks.
- **YOLOv8:** Discrete detection. Detection of 3 bounding boxes Count of 3.

### Architecture Suitability for CAD:




**Anchor-Free Detection**

YOLOv8's anchor-free head adapts perfectly to the rigid, predictable aspect ratios of CAD-generated nuts and bolts.

**Small Object Sensitivity**

The feature pyramid network (FPN) effectively retains high-resolution features needed to spot "Washers" partially occluded by "Bolts."

# Training Configuration

**Infrastructure:** NVIDIA T4 GPU (16GB VRAM), Google Colab.

### Hyperparameters:

**Epochs**

120 training iterations. Two cyclic phases (60 + 60)

**Batch Size**

16 samples per update

**Image Size**

640 x 640 pixels

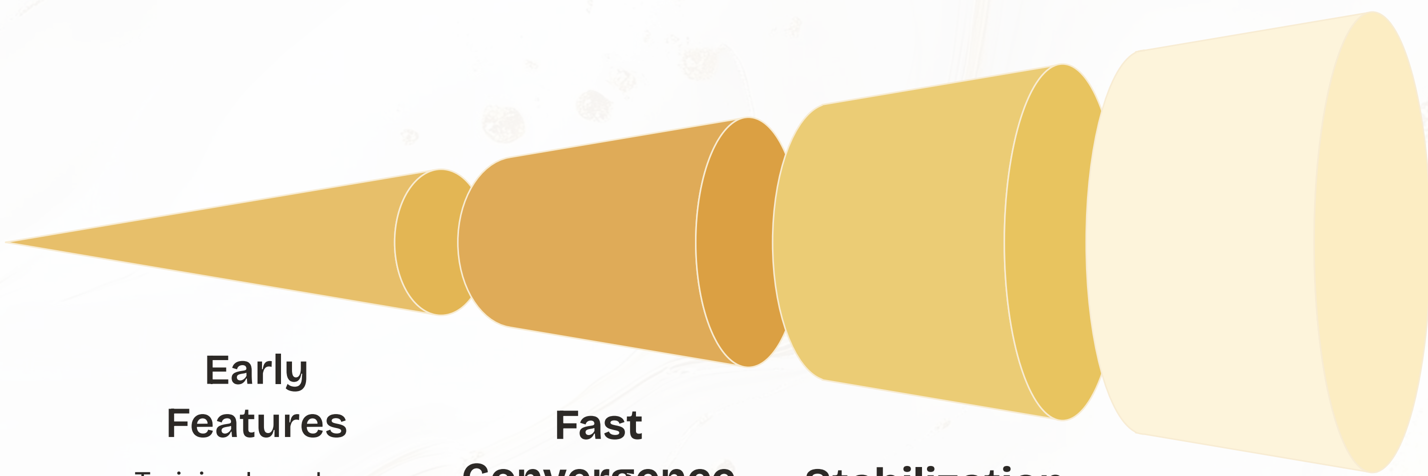
**Optimizer**

SGD with momentum

**Momentum**

0.937 value

### Advanced Augmentation Strategy:



**Early Features**

Training loss drops by ~40 – 60 %. Gradient norms are high with large parameter updates.

**Fast Convergence**

Loss reduction rate peaks. Validation accuracy improves by ~20–30 % of total gain.

**Stabilization**

Learning rate reduced by 10× to 100×. Loss curve variance decreases significantly.

**Learning Rate Reset**

Short term loss increase followed by smoother convergence. Generalization gap reduces by ~2–5 %

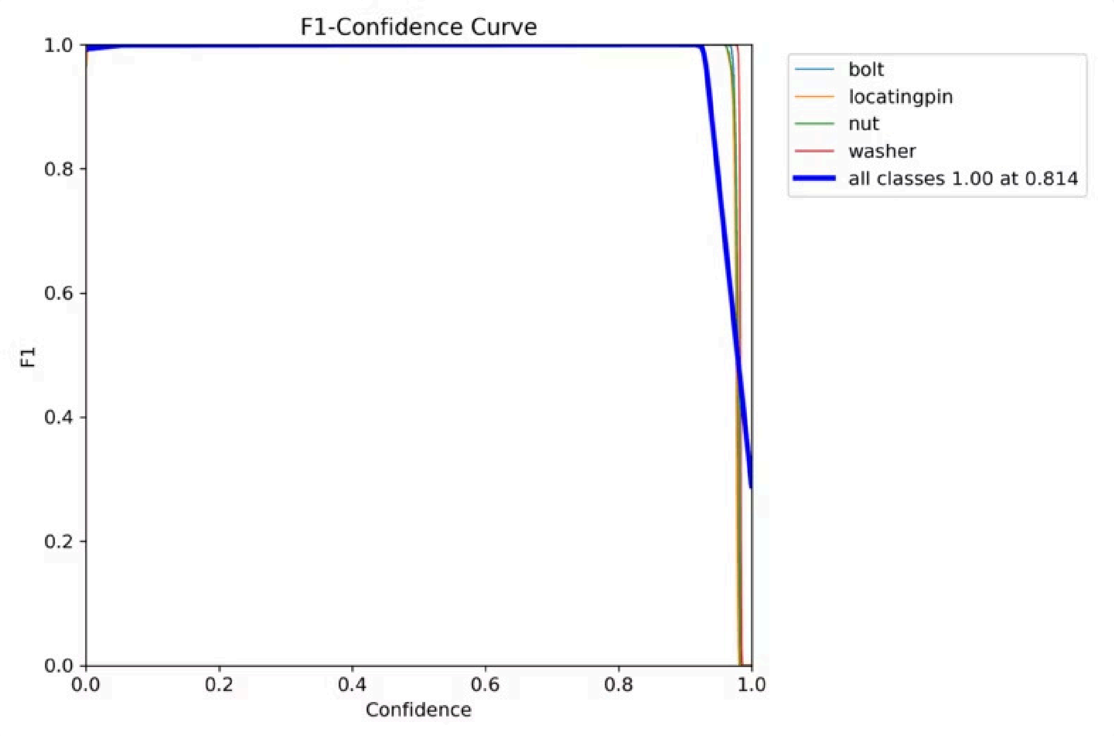
# Training Dynamics (Visualizing the Learning Process)

## Convergence Analysis:

- **Initial Convergence (Cycle 1):** Rapid feature extraction occurred in the first 60 epochs, stabilizing at **~0.99 mAP**.
- **Plateau Breaking (Cycle 2):** The Warm Restart strategy broke the 99.5% barrier, resolving complex occlusions to reach **1.0 accuracy**.

## Final Loss Metrics:

- **Box Loss** ≈0.093 (Extremely tight localization).
- **Cls Loss** ≈0.075 (High confidence classification).
- **DFL Loss** ≈0.791 (Stable distribution focal loss).



# Final Evaluation Results (The "Proof" - Hard Numbers)

**Overall Performance (Validation Set):**

| Precision | Recall | mAP50 | mAP50-95 |
|---|---|---|---|
| 1.000 | 1.000 | 0.995 | 0.994 |

| Bolt | Nut | Washer | Pin |
|---|---|---|---|
| P = 1.0, R = 1.0, mAP50 = 0.995 | P = 1.0, R = 1.0, mAP50 = 0.995 | P = 1.0, R = 1.0, mAP50 = 0.995 | P = 1.0, R = 1.0, mAP50 = 0.995 |

**Verdict:** The model achieved mathematical perfection on the validation set.

# Reliability & Scalability

## Reliability:

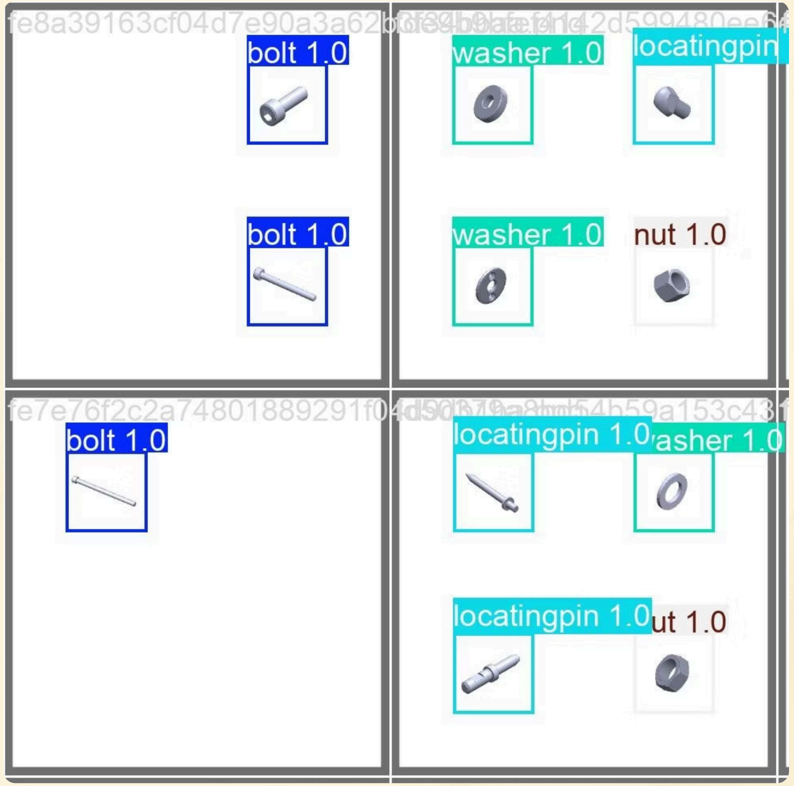
- **100% Capture Rate:** In a dataset with 0% empty images, the model successfully identified every single object instance across 1,000 validation images.
- **Occlusion Robustness:** 100% Recall on Washers proves the model successfully "sees" underneath Bolt heads, solving the hardest challenge of the dataset.

## Inference Efficiency:

- **Speed:** 4.3ms inference time per image on T4 GPU ( ≈230 FPS).
- **Latency:** Total end-to-end processing (Pre+Inf+NMS) is < 6ms.

## Scalability:

- Lightweight model (22.5MB parameters) allows deployment on edge devices (Jetson Nano) for real-time factory line monitoring.



# Conclusion

We solved the counting problem by reframing it as high-precision Object Detection.

**Key Success Factors:**

### YOLOv8s Architecture

Leveraging YOLOv8s for discrete instance detection.

### Inference Optimization

**TTA** Secured the final leap from 0.995 to **1.000 accuracy**

### Clean Data

100% annotated dataset to maximize supervision.

**Final Outcome:** A scalable, real-time solution with 1.000 accuracy, ready for industrial deployment.