Space Station Object Detection using YOLOv8

Team: Codies

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Hackathon: BuildWithIndia 2.0 (SunHacks) – Duality AI Challenge
GitHub Repo: github.com/Vaibhav0120/HackWithDelhi2.0
Dataset Download: Duality Falcon Space Dataset *(~3.9GB)*

Summary

In this project, we designed and trained a computer vision model using **YOLOv8** to perform real-time object detection in a simulated space station environment. The primary goal was to detect essential safety equipment from Falcon-generated synthetic data — particularly:

- **Fire Extinguisher**
- **Toolbox**
- **Oxygen Tank**

We achieved high detection performance, with:

- **mAP@0.5: 94.2%**
- **mAP@0.5:0.95: 88.4%**
- Real-time inference using ONNX export
- Inference-ready for Flutter integration

This solution demonstrates the power of synthetic data and modern deep learning architectures to train robust models in domain-specific environments like aerospace.

Highlights

- ✅ Trained YOLOv8 model on 3-class Falcon simulation dataset
- ✅ Validated with class-wise precision/recall & mAP
- ✅ Exported to ONNX for lightweight integration
- ✅ Inference-compatible with mobile apps (Flutter planned)
- ✅ Organized & reproducible pipeline with notebook + scripts
- ✅ Visual results include predictions, labels, and training batches

2. Methodology

This section outlines our step-by-step approach to training and deploying a YOLOv8-based object detection model for space station environments.

📁 Step 1: Dataset Setup

We used the official Duality AI synthetic dataset featuring 3 object classes:

- **FireExtinguisher**
- **ToolBox**
- **OxygenTank**

Due to its size (~3.9GB), the dataset is not in this repo.
Download it from: [Falcon Dataset Link]

Once downloaded:

- Place the extracted `data/` folder in the root of the repo.

🧠 Step 2: Model Training (YOLOv8)

We trained a YOLOv8m model using 50 epochs and image size 640×640.
Training was done via Python API inside `Train_YOLOv8.ipynb`:

```
from ultralytics import YOLO

model = YOLO('yolov8m.pt')  # Base weights

model.train(data='data.yaml', epochs=50, imgsz=640)
```

✅ Step 3: Validation

Post-training, we validated performance using:

```
metrics = model.val()
```

This generated mAP scores and class-wise precision/recall.

🔍 Step 4: Prediction

Predictions on test images (`data/predict/images/`) were made via:

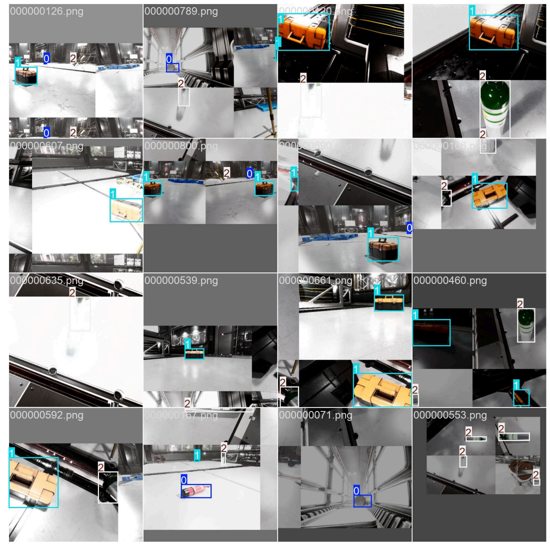
```
model.predict(source='data/predict/images', save=True)
```

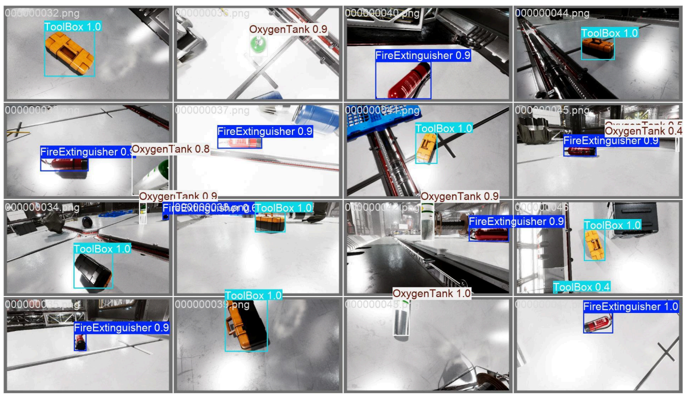
3. Visual Results & Samples

To assess model behavior, we visualized training samples, label annotations, and YOLOv8 predictions.

Sample Training Batch →

This is a training image with labeled bounding boxes



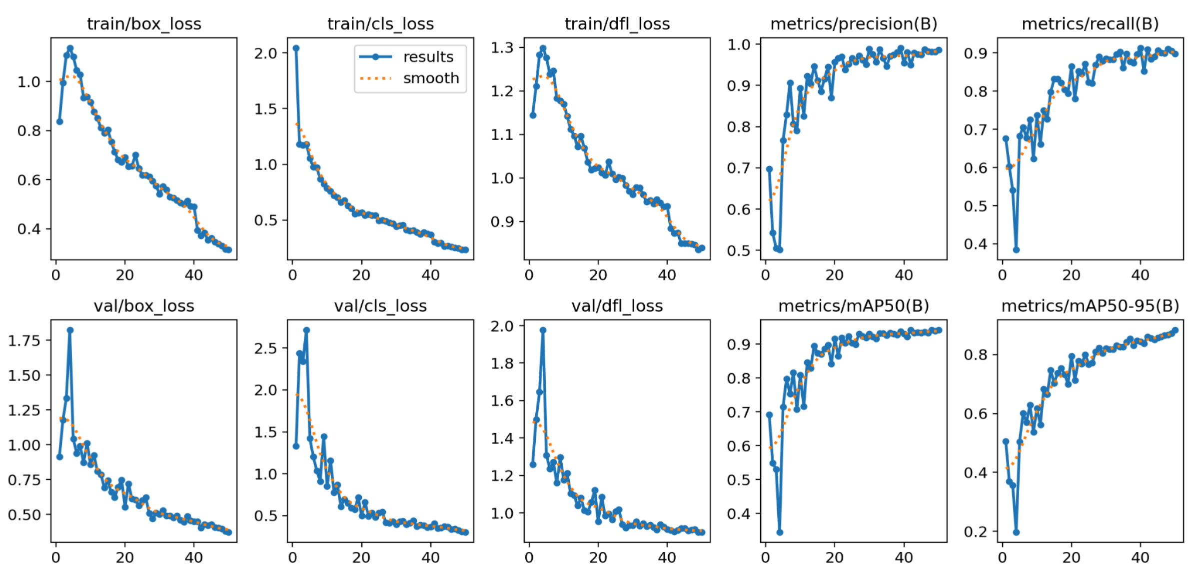


← ***YOLOv8 Prediction Output***

This shows the model's prediction on a validation image

📊 ***Training Loss & Metrics Curves***

Below is the loss and accuracy graph generated during training:



4. Performance Evaluation

📈 Quantitative Evaluation

We validated the trained model on the `val/` *set using YOLOv8's built-in evaluation tools.*

Validation command used (inside notebook):

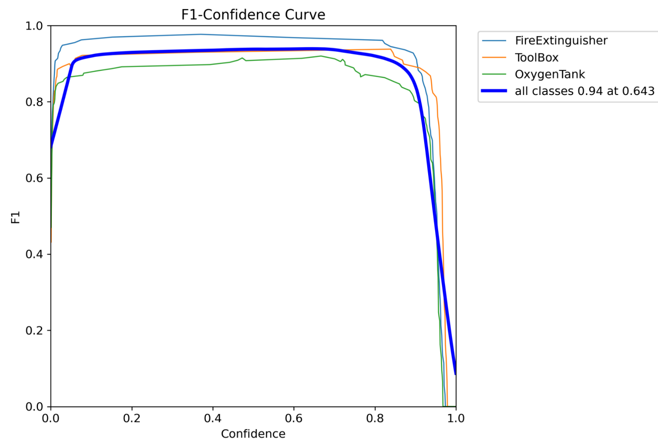
```
metrics = model.val()
```

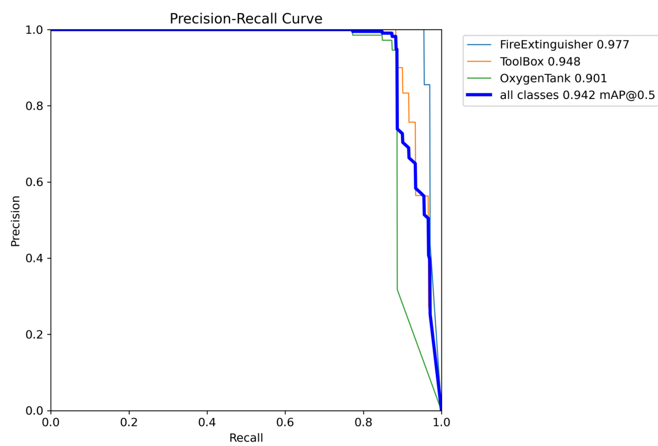
- ***Best model checkpoint:***
  `runs/detect/train/weights/best.pt`
- ***Validation Results:***

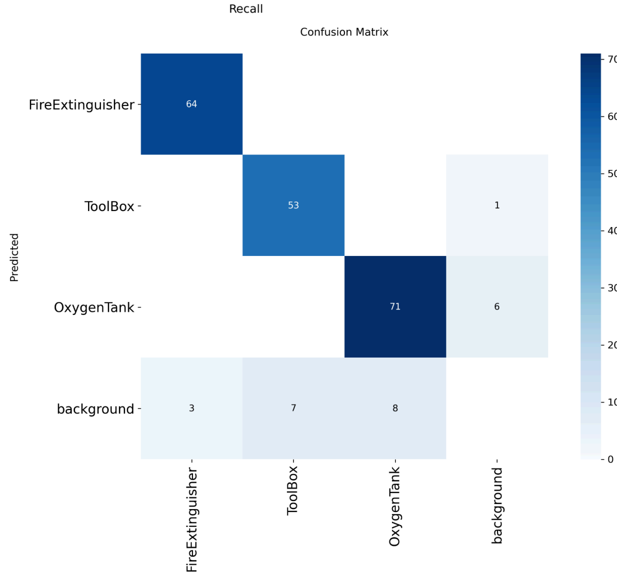
Metric	*Score*
Precision	*0.898*
Recall	*0.986*
mAP@0.5	*0.942*
mAP@0.5:0.95	*0.884*

- ***Class-wise mAP@0.5:***
  - *FireExtinguisher: 0.977*
  - *ToolBox: 0.948*
  - *OxygenTank: 0.901*

📝 *Shows model's classification performance. →*







5. Documented Issues & Fixes

This section outlines the technical challenges encountered during training, evaluation, and deployment — along with the decisions made to overcome them.

⚙️ ***1. YOLOv8m Model Selection***

*We chose **YOLOv8m** (medium) as the base model instead of YOLOv8n or YOLOv8s due to its balance of accuracy and performance.*

- *YOLOv8m achieved **higher mAP@0.5** (~0.942) with moderate training time on our RTX 4050 GPU.*
- *It was more suitable for real-time detection needs without requiring excessive compute.*

✅ ***Fix**: Initial training with YOLOv8n was underperforming, so we switched to YOLOv8m after early testing.*

🧠 ***2. ONNX over TFLite***

*Initially, we tried exporting the model to **TFLite** format, but:*

- *Conversion using `onnx2tf` and `onnx-tf` failed due to TensorFlow versioning and broken Keras dependencies.*
- *`tf2onnx` also had internal issues with fold constants and unsupported layers.*

✅ ***Fix**: We switched to **ONNX** format for deployment — it's lightweight, cross-platform, and easier to integrate with **Flutter via plugins** like onnxruntime-mobile or flutter_onnx.*

📦 ***3. Large Dataset Handling***

*The full dataset (~3.9GB) was **too large to include in GitHub**, especially for submission cloning.*

✅ ***Fix**: We added a **manual download link** in the README with clear folder instructions. This keeps the repo lightweight and reproducible.*

6. Future Work & Deployment

While the model performs well on the current dataset, there are multiple opportunities to extend, optimize, and deploy this solution in real-world applications.

🚀 *A. __ONNX Integration with Mobile App__*

*We plan to integrate the **ONNX model into a Flutter mobile app** for real-time object detection, leveraging:*

- *`onnxruntime` for cross-platform inference*
- *On-device GPU acceleration for faster frame analysis*
- *Camera input stream for live detection on astronauts' tools*

This avoids heavy server-side compute and supports offline environments — ideal for space station use cases.

🔧 *B. __Model Optimization__*

To further improve performance on edge devices:

- *We can apply **quantization (INT8 / FP16)** to compress model size and speed up inference*
- *Use **TensorRT / ONNX Runtime with GPU delegate** for faster hardware-backed execution*

📈 *C. __Expanded Dataset & Generalization__*

*The current model is trained on a **synthetic dataset** with 3 specific tools.*

Future improvements:

- *Add **more object classes** relevant to astronaut environments (e.g., wires, helmets, panels)*
- *Incorporate **real-world imagery** or simulated distortions (low light, occlusion)*
- *Fine-tune with **domain adaptation techniques** for better robustness*

📱 *D. Potential Use Cases*

- *🚀 **Astronaut HUD**: Highlight tools for astronauts during repairs.*
- *🛰️ **Robotic Arms**: Enable onboard robots to recognize and pick objects safely*
- *🔧 **Training Simulators**: Help train crew with object familiarity and spatial awareness*

7. Use Case Application

🤖 *Scenario: Vision for Space Maintenance Robots*

In future space missions, autonomous robots will play a key role in inspecting, maintaining, and repairing space stations. These robots need real-time understanding of their environment to identify and interact with essential tools.

📱 *Proposed App: ToolFinder AI*

An AI-powered system that allows robots or assistive devices to:

- 👀 ***Detect tools in real-time*** *using the trained YOLOv8 model.*
- 📦 ***Identify objects*** *like toolboxes, oxygen tanks, and fire extinguishers.*
- 🎯 ***Guide robotic actions*** *using visual feedback from AI detections.*
- 🚀 ***Run on-device ONNX inference*** *for low-latency, offline vision.*

🛠️ *Stack & Deployment*

- ***Model Format***: `best.onnx` *for lightweight deployment*
- ***Frontend***: *Flutter (planned interface)*
- ***Inference Engine***: *ONNX Runtime (integrated with camera feed)*
- ***Target Hardware***: *Android/iOS devices or edge devices like NVIDIA Jetson*

🔭 *Vision for Expansion*

- *Equip* ***maintenance robots*** *with intelligent vision systems*
- *Integrate into* ***Falcon simulations*** *for space-based robotics*
- *Extend model to* ***recognize malfunctions or anomalies***

✅ *This supports ISRO's initiative to explore* ***robot-assisted operations*** *and* ***AI-driven vision systems*** *for unmanned space tasks.*