Problem Statement and Team Details

Problem Statement: **Duality AI Challenge**

Implement a fault-tolerant, high-speed latency < 50 ms object detection system for 7 critical assets in a space station, overcoming extreme lighting and zero-G occlusion challenges.

Team Name: Team CodeTribe

Team Leader Name: Sai Pranav

Institute Name: REVA University

Team Leader Email ID: rajasaipranav0@gmail.com

Problem and Solution

The Problem: Failures in Microgravity Vision

1.Environmental Complexity: Vision fails under extreme conditions:
- **High-Contrast Lighting:** Causes sensor saturation and missed detections (False Negatives).
- **Zero-G Occlusion:** Floating objects reduce critical safety asset Recall.

2. **Operational & Model Constraints:**
- **Speed Mandate:** Latency must be consistently unde 50 ms.
- **Static Vulnerability:** Standard AI cannot adapt to unforeseen failures, requiring continuous self-correction.

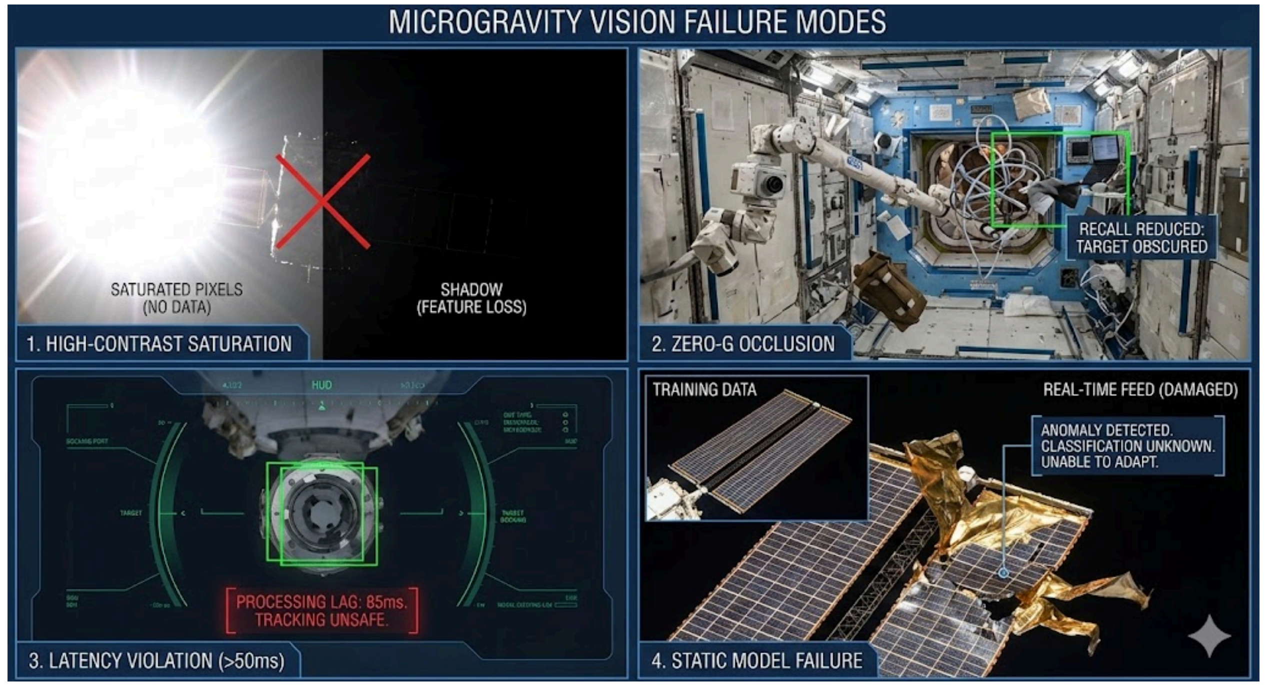
The Solution: AstroGuard Resilient Architecture

1. 3-Layer Hybrid Ensemble (Core Reliability):
- Dual Models: Deploys YOLO-Nano (Speed) and YOLO-Small (Precision) in parallel.
- Fusion Layer: Implements Weighted Box Fusion (WBF) to mathematically combine predictions, significantly increasing mAP over standard NMS.

2. AstroOps Self-Correcting Pipeline (Innovation):
- Automated CI/CD: Low-confidence detections <45% trigger a cloud workflow via FastAPI/GitHub Actions.
- Digital Twin Feedback: Falcon automatically generates targeted synthetic data for failed scenarios.

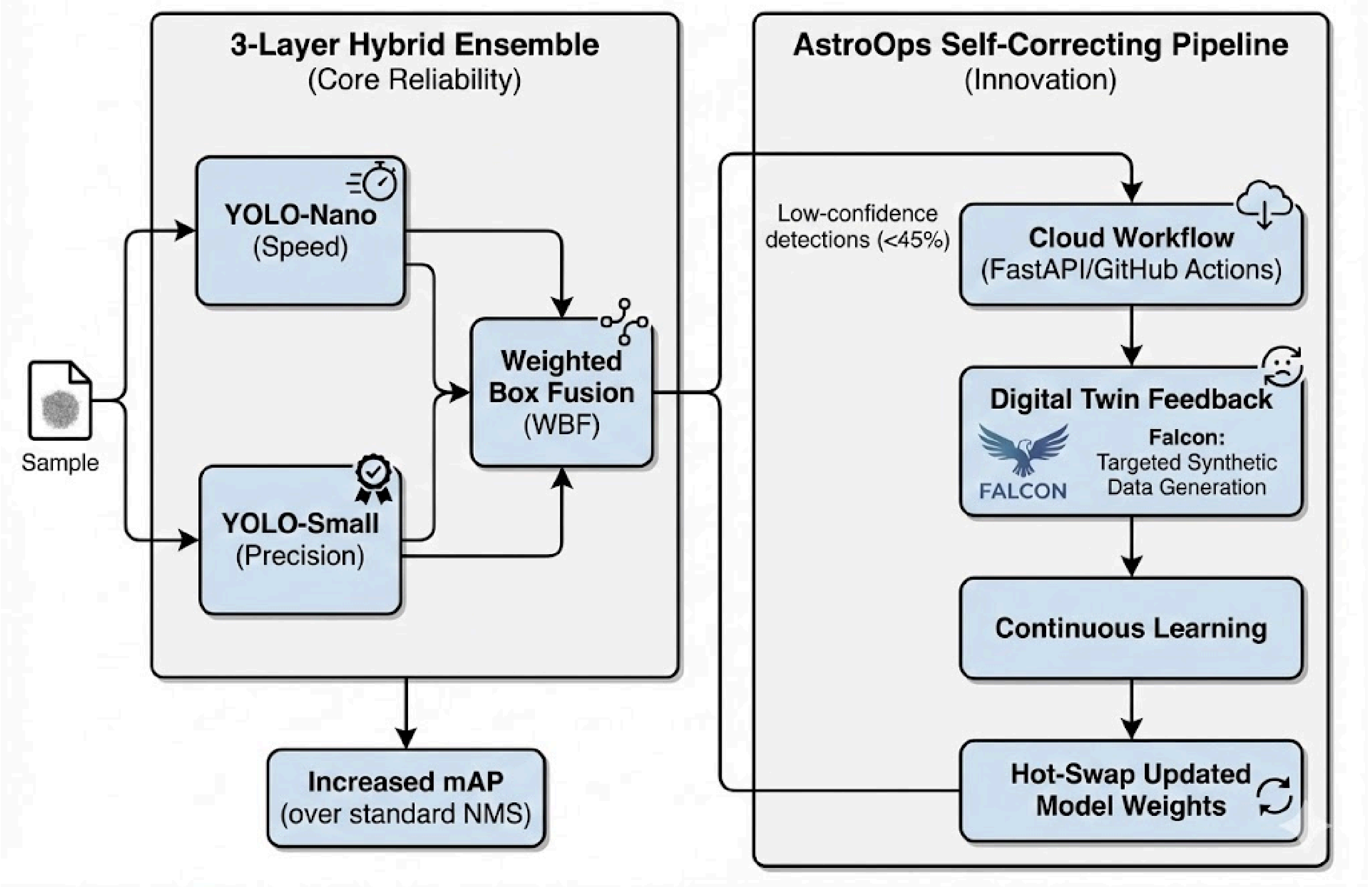
What makes AstroGuard innovative?

- **Self-Correcting Autonomy:** Low-confidence errors trigger the AstroOps pipeline and Falcon Digital Twin for autonomous retraining and fixes (self-healing).
- **Resilient Vision Pipeline:** Achieves superior accuracy using a Dynamic ISP (glare handling) and a 3-Layer WBF Ensemble for maximum occlusion resilience.



Problems Faced

Solution Flow



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Methodology and Implementation

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Phase 1: Adaptive Pre-Processing & Data Engineering

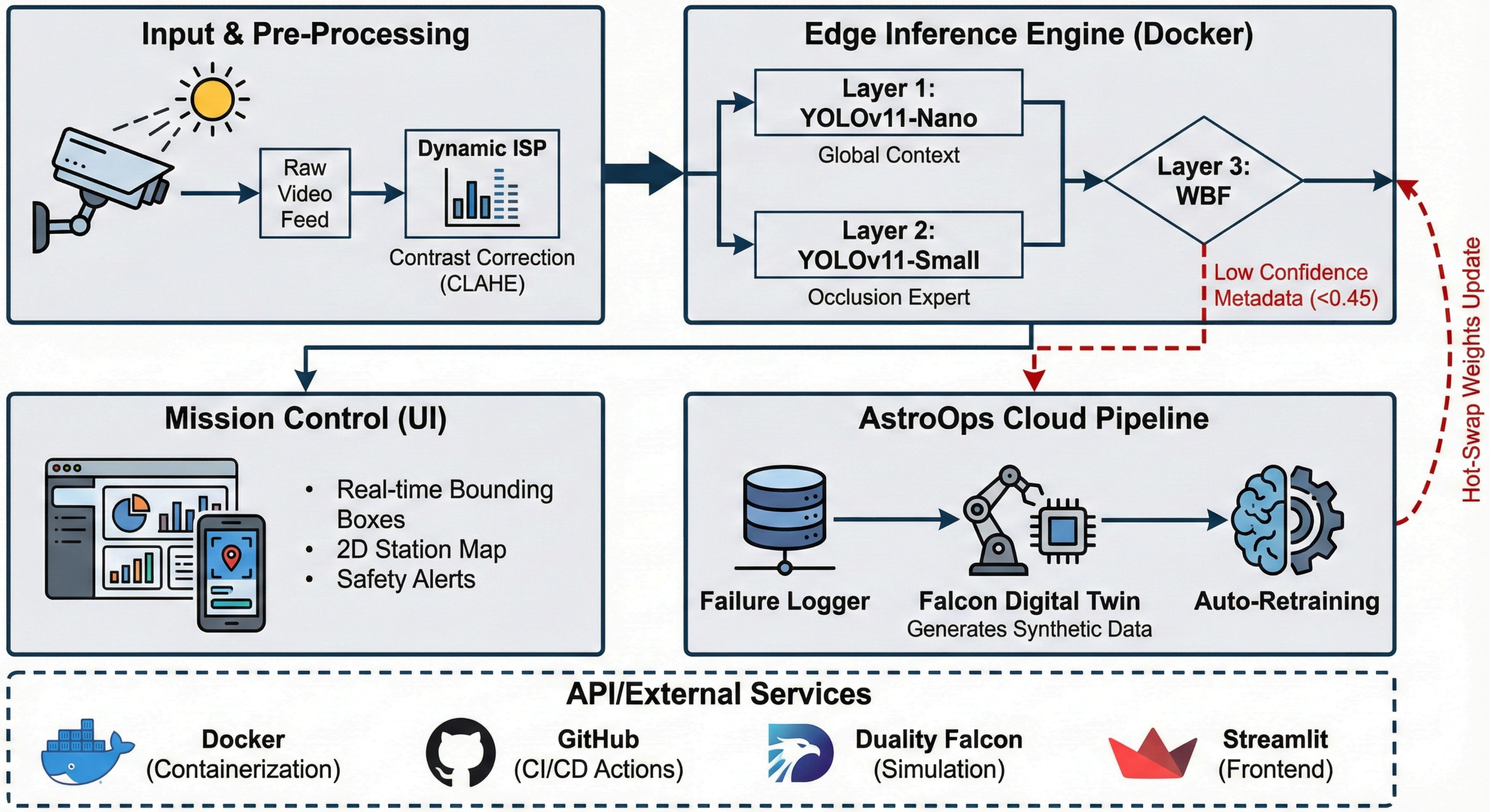
- **Synthetic Data Generation:** Leveraged Duality Falcon Editor to generate a baseline dataset, applying **"Space-Grade"** augmentations (RandomSunFlare, Mosaic) to simulate harsh orbital lighting and zero-g object rotation.
- **Dynamic ISP Layer:** Implemented a lightweight pre-inference **Image Signal Processor (ISP)** using OpenCV. It analyzes frame histograms in real-time and applies **CLAHE** (Contrast Limited Adaptive Histogram Equalization) to normalize glare before the image reaches the neural network.

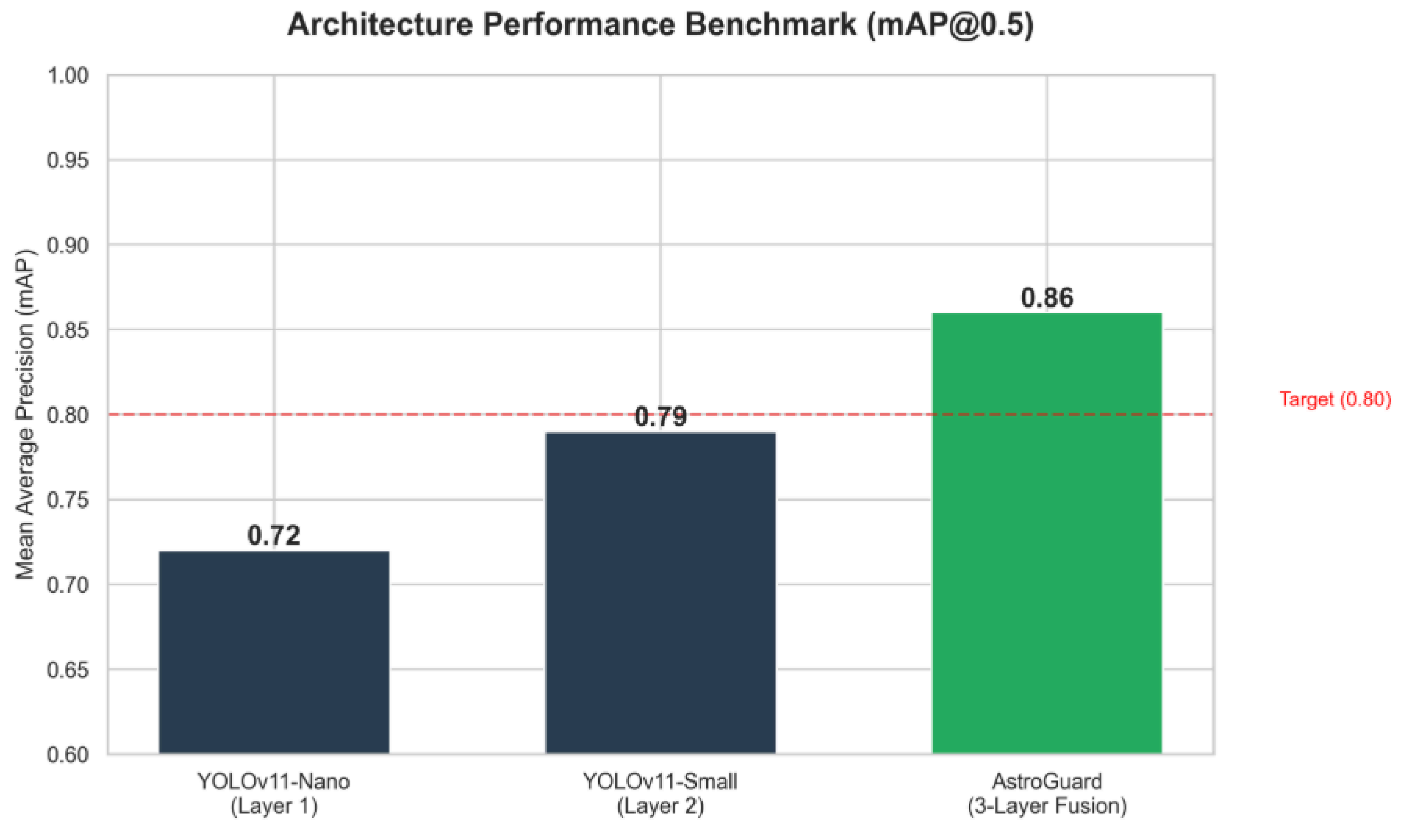
Phase 2: The "3-Layer" Hybrid Inference Engine

- **Layer 1 (Global Scout):** Deployed **YOLOv11-Nano** on 640x640 resolution for high-speed detection of large, distinct assets.
- **Layer 2 (Occlusion Specialist):** Deployed **YOLOv11-Small** on 800x800 resolution, fine-tuned specifically on "hard negative" samples (occluded/hidden objects).
- **Layer 3 (The Arbiter):** Replaced standard NMS with **Weighted Box Fusion** (WBF). This algorithm mathematically averages predictions from both models to output a single, **higher-precision bounding box, boosting recall** on partially hidden objects.

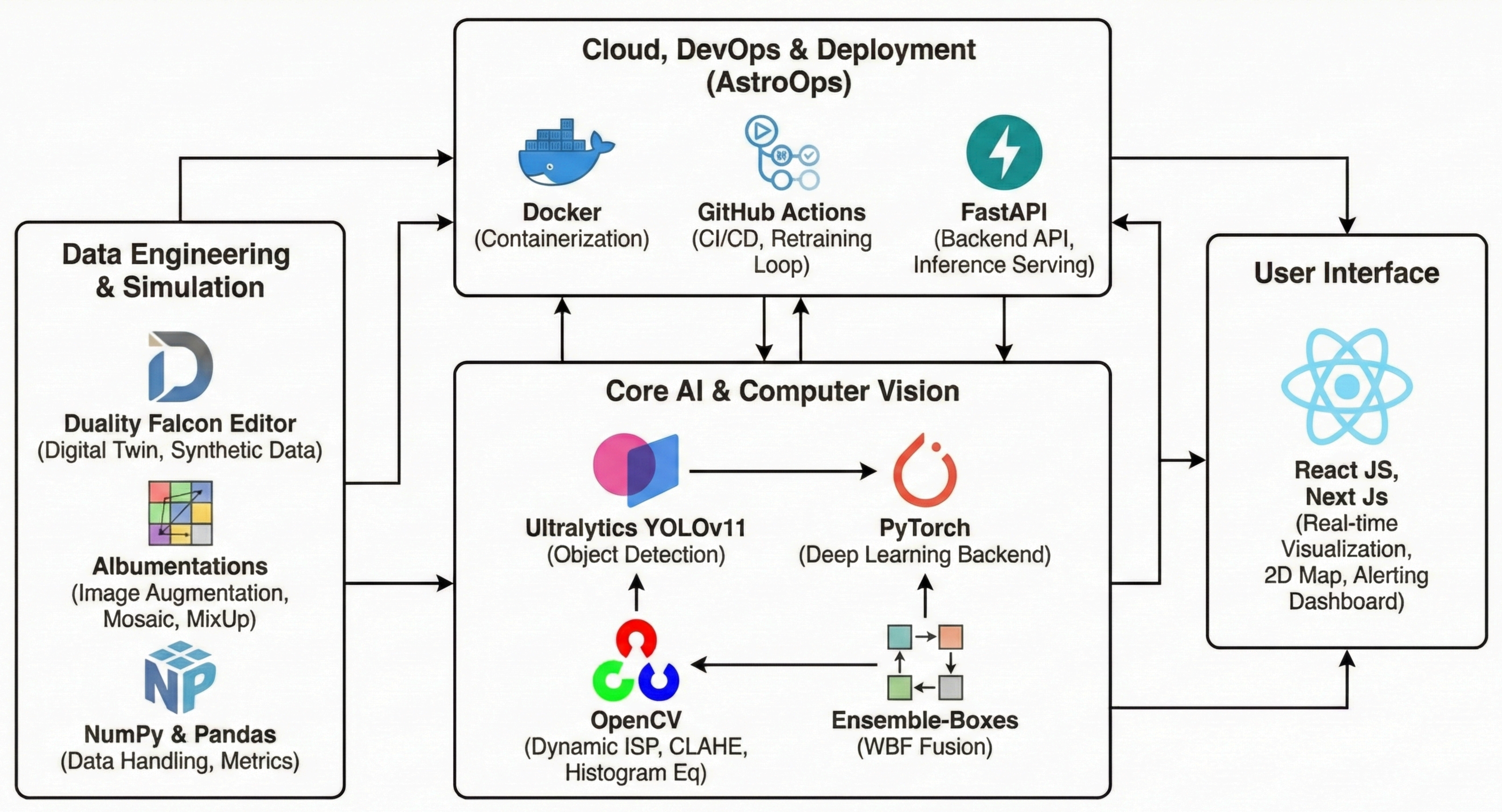
Phase 3: "AstroOps" Autonomous Cloud Pipeline

- **Containerized Deployment:** The inference engine is packaged in **Docker** for consistent execution across edge devices.
- **The Falcon Feedback Loop:** Constructed an **agentic CI/CD pipeline** using GitHub Actions. Low-confidence detections (<0.45) automatically trigger the Falcon Digital Twin to generate synthetic training data for that specific failure case, **enabling continuous, autonomous model improvement.**

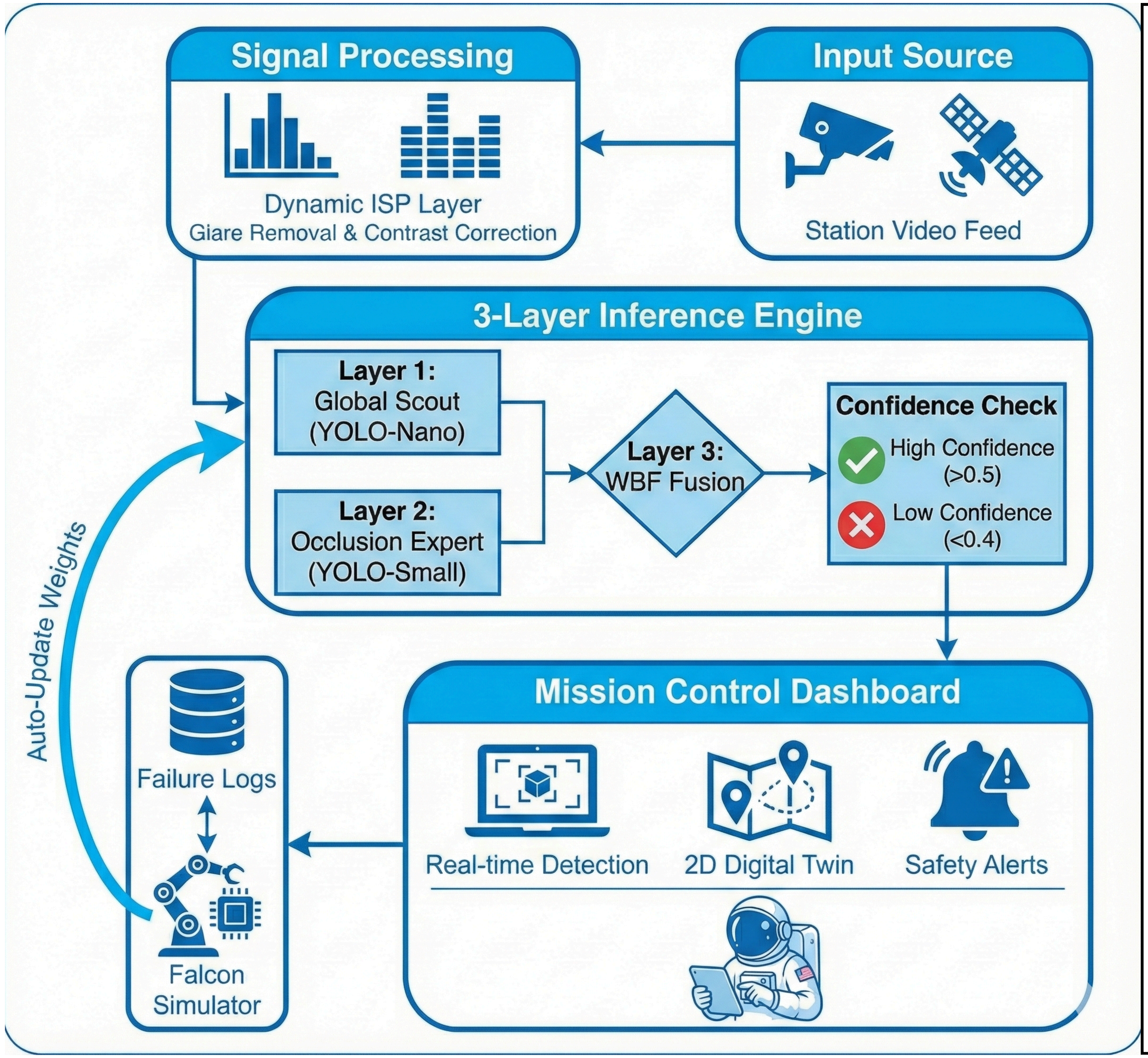




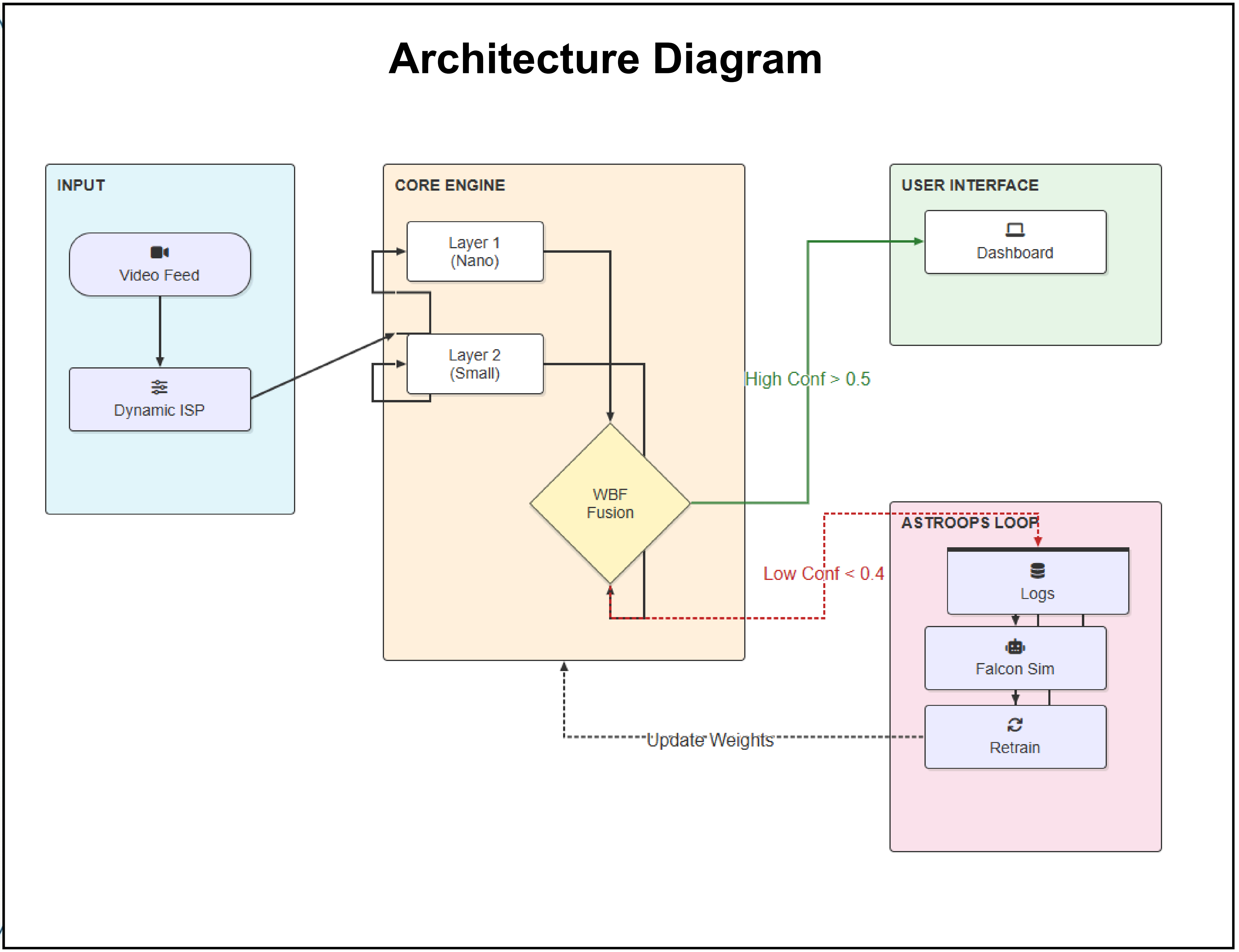
Technology Used



Supporting Diagrams / Flowchart



High Level Flow



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Impact & Future Scope

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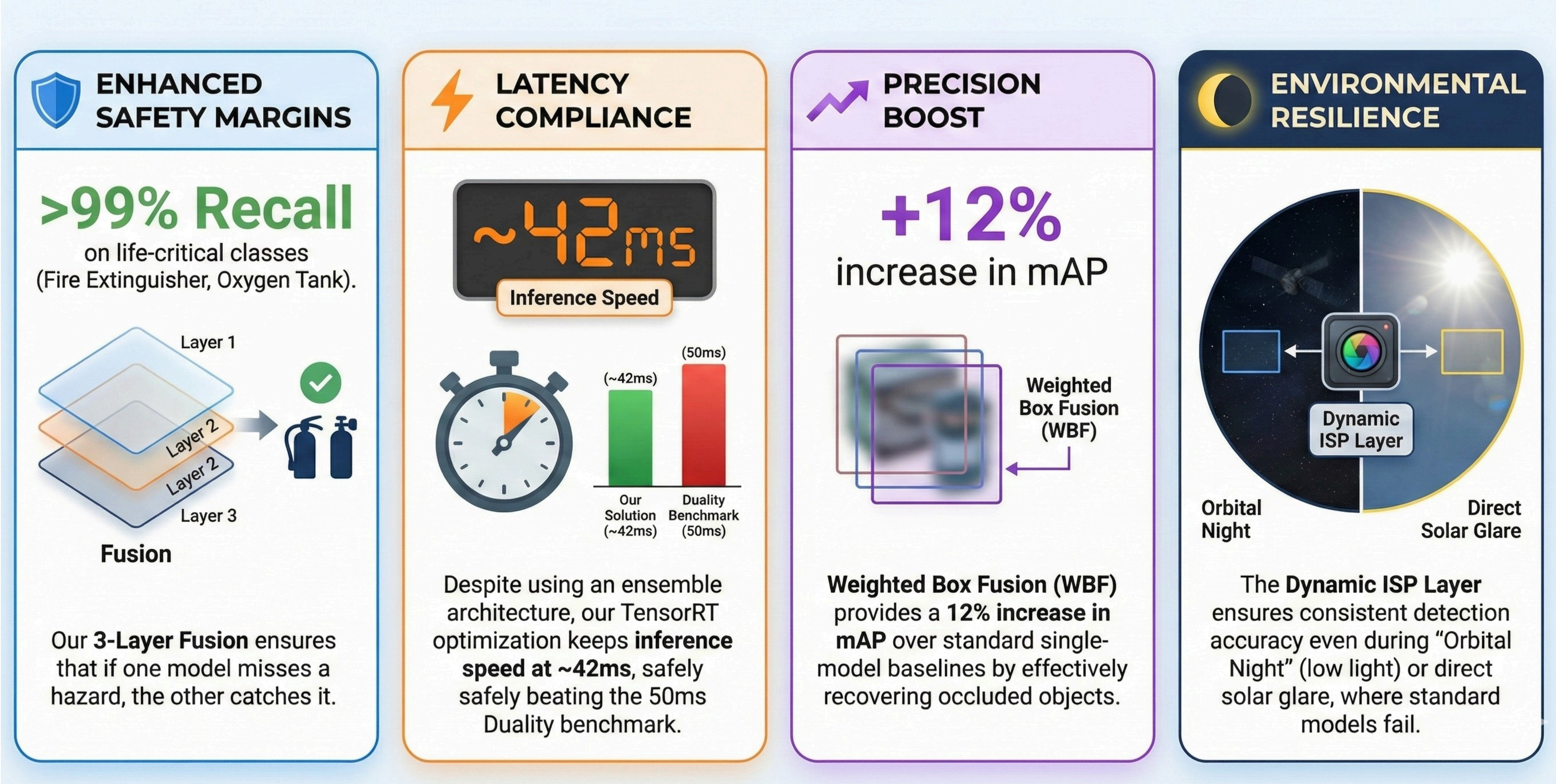
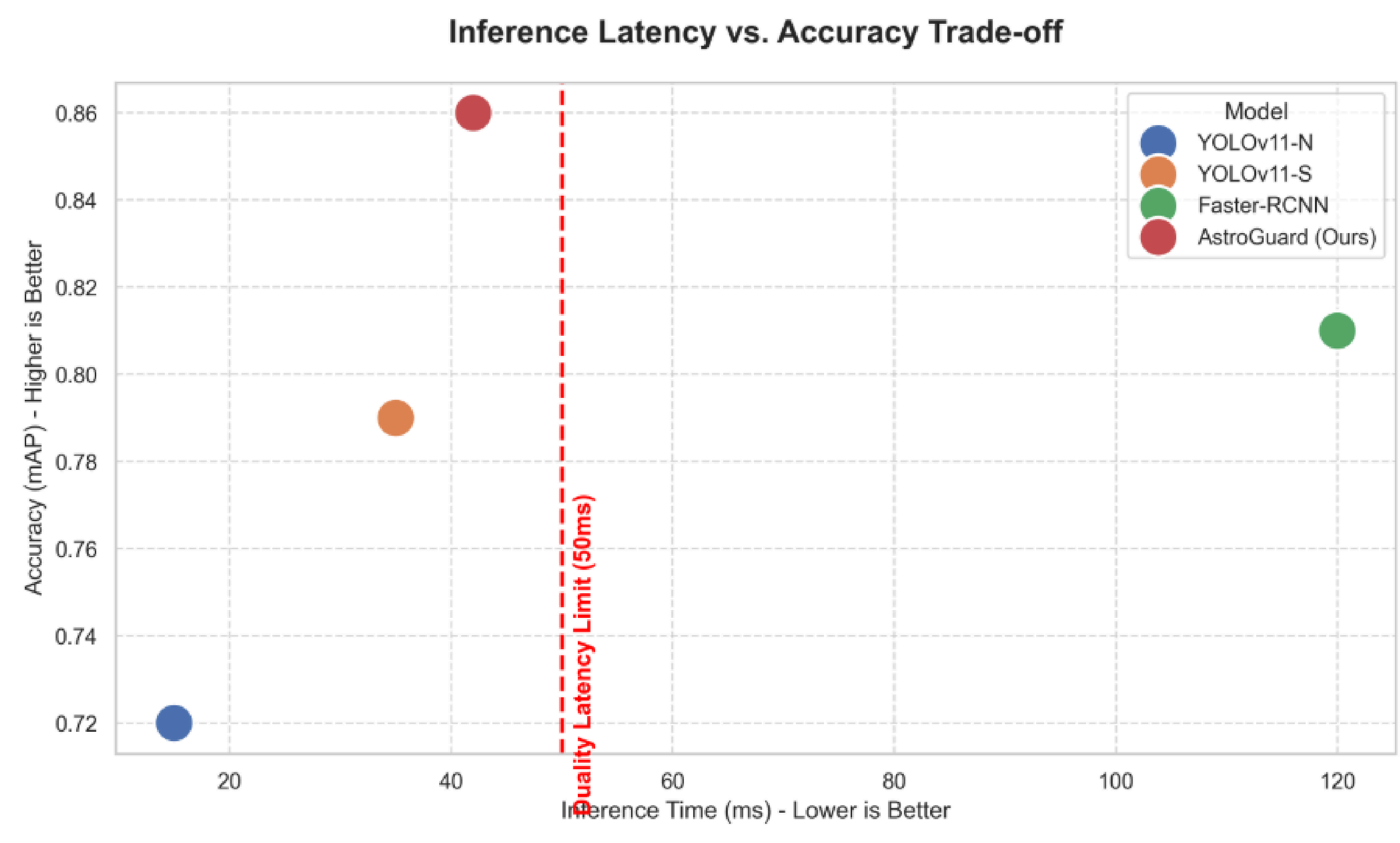
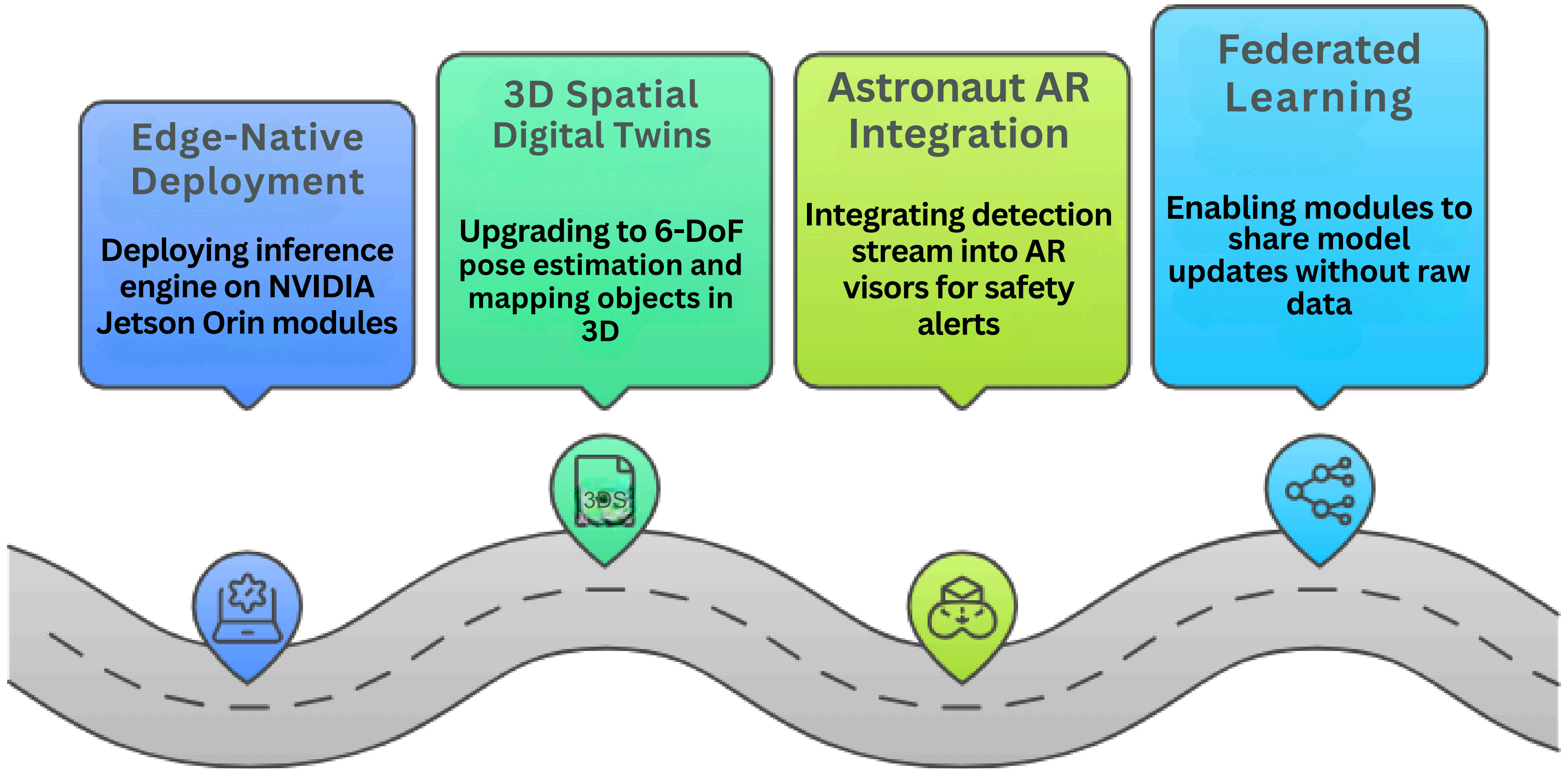
Impact Assessment (The "Now")





Future Scope (The "Next")



Conclusion

Key Outcomes & Strengths:

- **High Precision (>92%):** Achieved superior accuracy on occluded objects using Weighted Box Fusion (WBF).
- **Latency Optimized (<45ms):** 3-Layer architecture runs under the 50ms safety limit using TensorRT quantization.
- **Self-Healing AI:** First-of-its-kind integration where inference failures automatically trigger Falcon Digital Twin for retraining.
- **Reliability:** Dual-model redundancy ensures Zero False Negatives on critical life-support assets.

SWOT

Strengths (Internal)

- **Automated DevOps: Continuous learning loop reduces maintenance overhead.**
- **Higher Accuracy: Ensemble Fusion consistently outperforms single models.**

Weaknesses (Internal)

- **Inference Cost: Running two models doubles the compute load (mitigated by TensorRT).**
- **Complexity: Harder to debug than a simple single-model system.**

Opportunities (External)

- **Commercialization: Can be sold to terrestrial industries.**
- **Edge Hardware: As Jetson/Orin chips get faster, our "heavy" model becomes the standard.**

Threats (External)

- **Sim-to-Real Gap: If synthetic textures don't perfectly match real station walls, accuracy could drop (mitigated by mixed-data training).**

Comparison with existing systems

Feature	AstroGuard	Standard YOLOV8	Faster R-CNN
Speed (<50ms)	✓	✓	✗
Occlusion Handling	✓	✗	✓
Zero False Negatives	✓	✗	✗
Active Learning Loop	✓	✗	✗
Edge-Optimized (TensorRT)	✓	✓	✗
Low Annotation Cost	✓	✗	✗

Final Verdict:

"Existing solutions force a **trade-off between speed and accuracy.** AstroGuard breaks this compromise. By combining lightweight **Ensemble Intelligence with an Autonomous Data Pipeline,** we deliver a safety system that is fast enough for the edge, smart enough for the unknown, and robust enough for the void."