

Bridging the Sim-to-Real Gap: A Hierarchical Deep Reinforcement Learning Architecture for Autonomous Navigation on Embedded Edge Hardware

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The Problem: Why TinyML Navigation?

- Context: Navigation in unstructured environments.
- The Conflict:
 - Classical Methods (PID/APF): Fast but brittle; stuck in Local Minima.
 - Deep Learning (DRL): Adaptive but computationally expensive (GPUs).
- Research Question:
 - Can we run a complex Deep Q-Network on a \$5 microcontroller (ESP32)?

AI Theoretical Foundation

- Markov Decision Process (MDP):
 - State (S): 3 Ultrasonic distances (Normalized 0.0 - 1.0).
 - Action (A): Discrete {Forward, Left, Right}.
 - Reward (R): +100 (Goal), -50 (Crash), -0.1 (Time penalty).

- The Bellman Equation (Q-Learning):

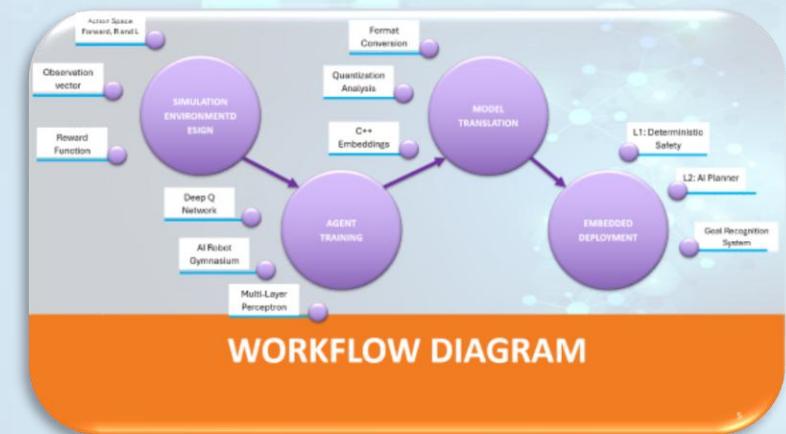
$$Q(s, a) = r + \gamma * \max Q(s', a')$$

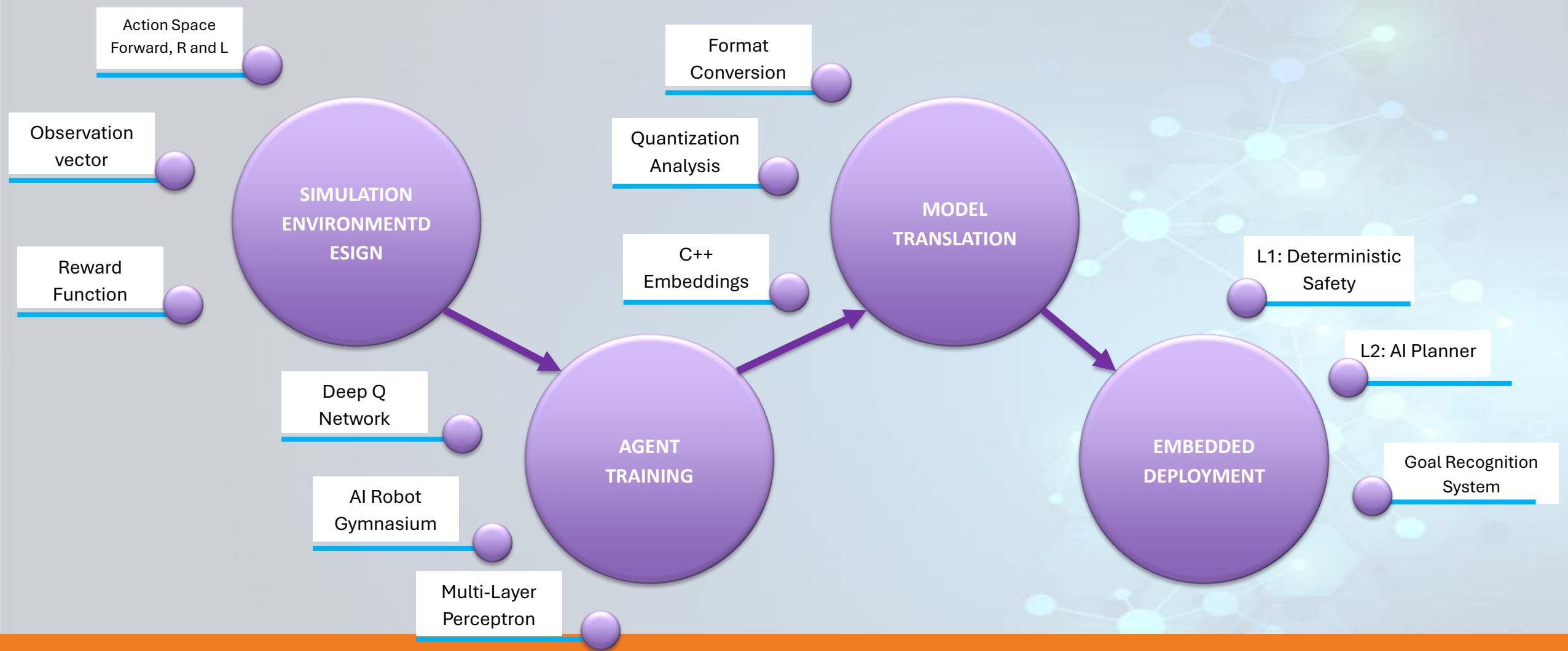
- Loss Function (Temporal Difference):

$$L = E[(Target - Prediction)^2]$$

Methodology: Sim-to-Real Pipeline

- System Architecture (See Block Diagram):
- 1. Simulation (Digital Twin):
 - OpenAI Gymnasium + Ray Casting.
- 2. Training:
 - Stable-Baselines3 (DQN Agent).
- 3. Model Translation Pipeline:
 - PyTorch -> ONNX -> TensorFlow Lite -> C++ Byte Array.
- 4. Deployment:
 - ESP32 Inference Engine (32ms per loop).





WORKFLOW DIAGRAM

Challenges & Engineering Solutions

- Challenge 1: Quantization Collapse
 - Problem: Int8 quantization (15KB) lost precision.
 - Symptom: Robot spun in circles (output constant 'Turn Right').
 - Solution: Enforced Float32 precision (60KB).
- Challenge 2: The Mirror Brain
 - Problem: Sim wiring [Right, Front, Left] != Real wiring.
 - Symptom: Robot turned INTO walls.
 - Solution: Software remapping of input vector.

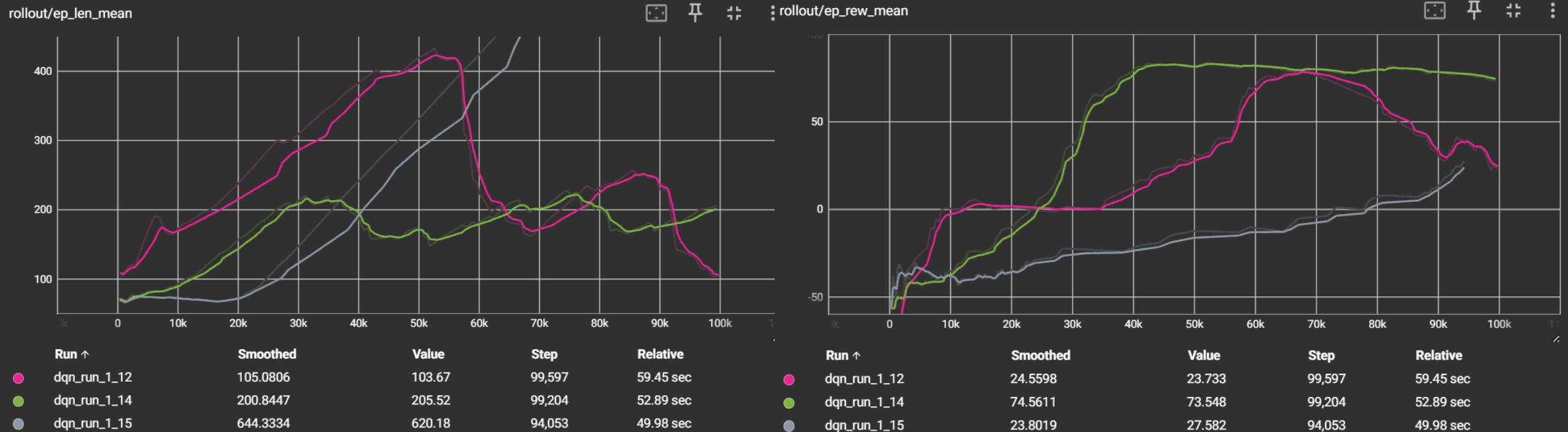
The Solution: Hierarchical Control

- Hierarchical Control Architecture (Hybrid AI):
- Layer 1: The Reflex (Safety)
 - If Distance < 15cm: Force Turn (Deterministic).
- Layer 2: The Planner (Intelligence)
 - If Safe: Query Neural Network (Probabilistic).
- Layer 3: The Mission (Success)
 - If IR Sensor == Black: STOP Motors.

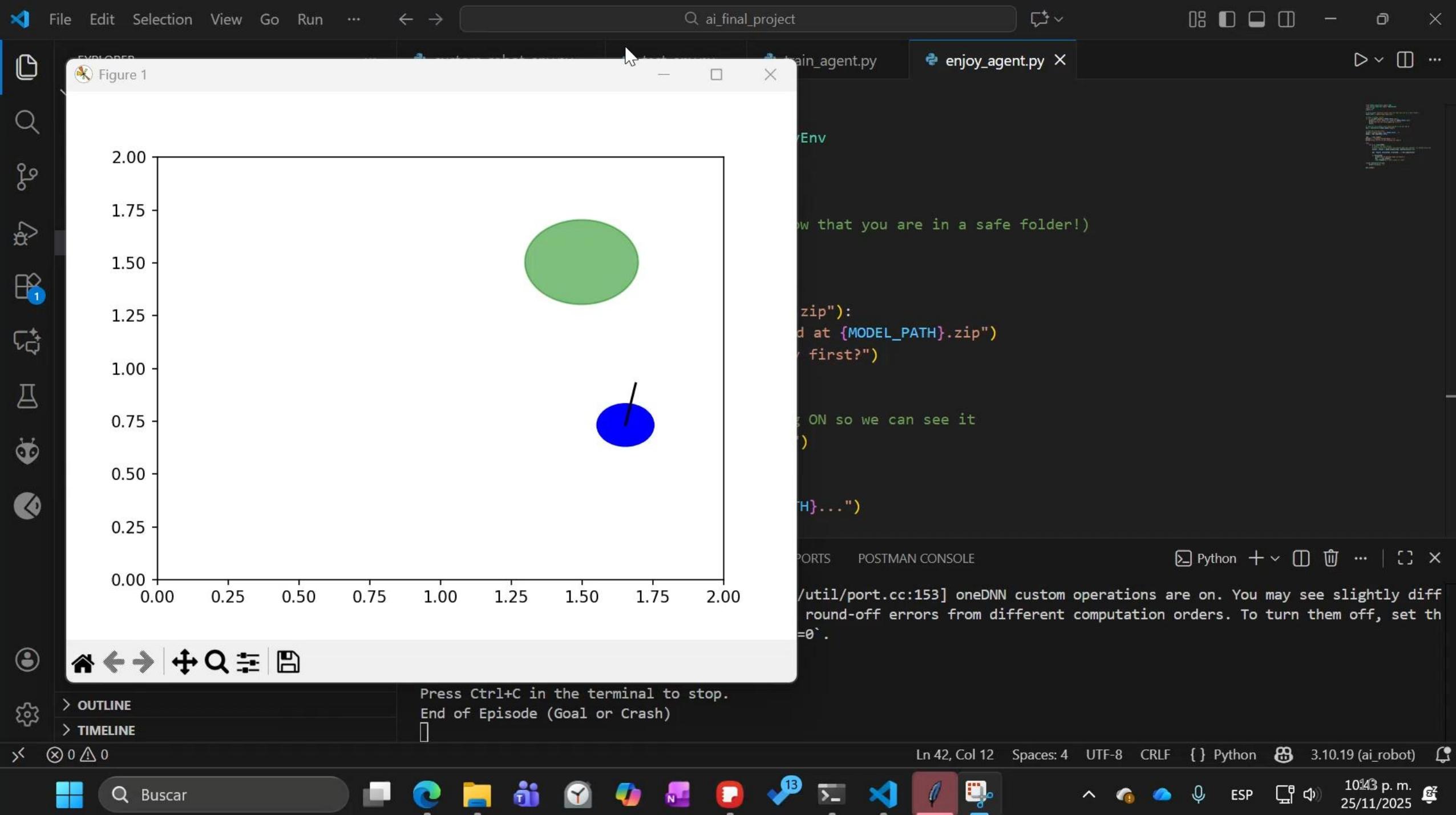
Experimental Results

- Training Analysis (See Graphs):
- 1. The Failure (Pink):
 - Catastrophic Forgetting due to high Learning Rate.
- 2. The Coward (Lime):
 - Reward Hacking (spinning to avoid death).
- 3. The Success (Green):
 - Steady S-Curve Convergence.
 - Reward Plateau at +80.
 - Key: Extended Exploration (40k steps) + Lower LR.



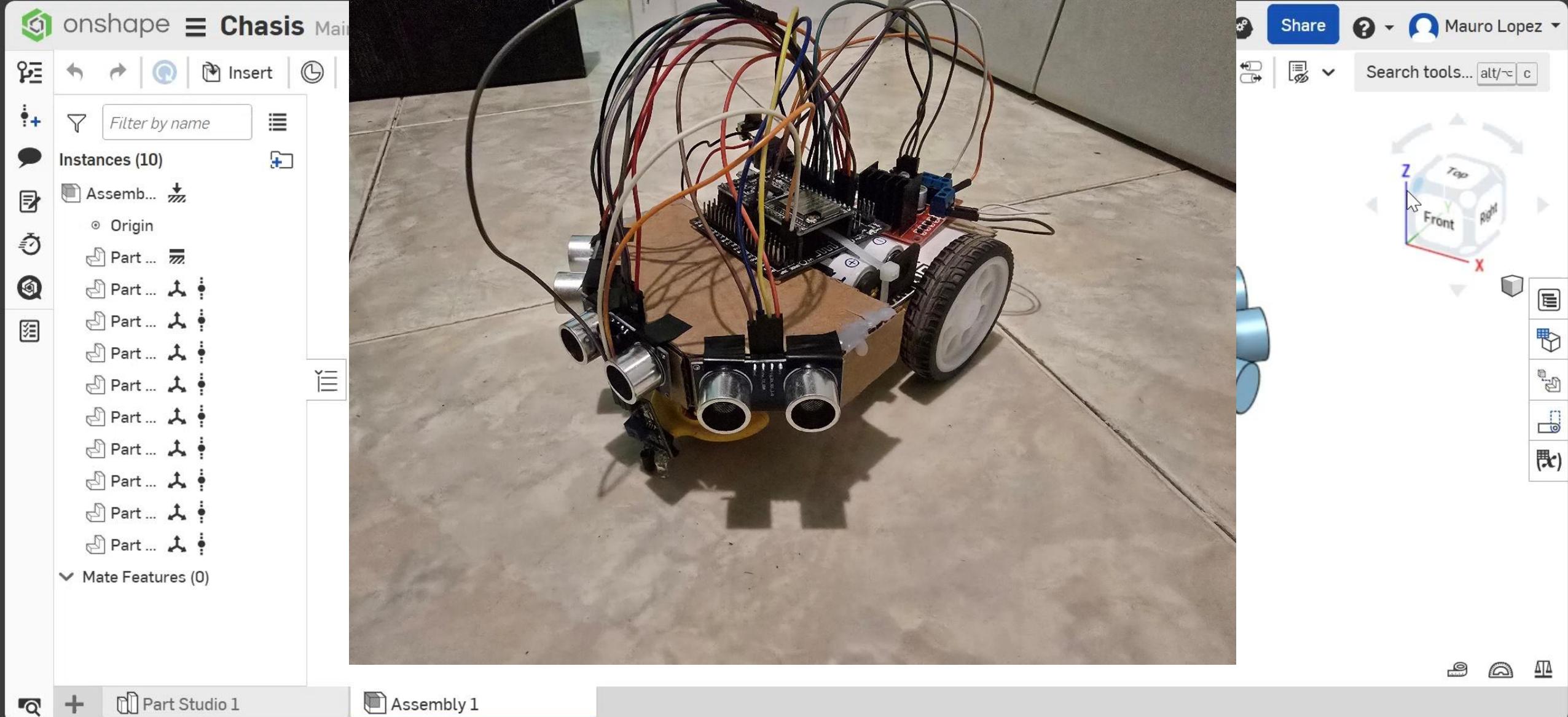


TENSORBOARD



Hardware conections

Component	Pin Name	ESP32 Pin
Left Sensor (-45°)	Trig	GPIO 13
	Echo	GPIO 12
Front Sensor (0°)	Trig	GPIO 14
	Echo	GPIO 27
Right Sensor (+45°)	Trig	GPIO 26
	Echo	GPIO 25
L298N Motor Driver	IN1 (Left Motor)	GPIO 33
	IN2 (Left Motor)	GPIO 32
	IN3 (Right Motor)	GPIO 18
	IN4 (Right Motor)	GPIO 19
	ENA / ENB	Jumpers on 5V

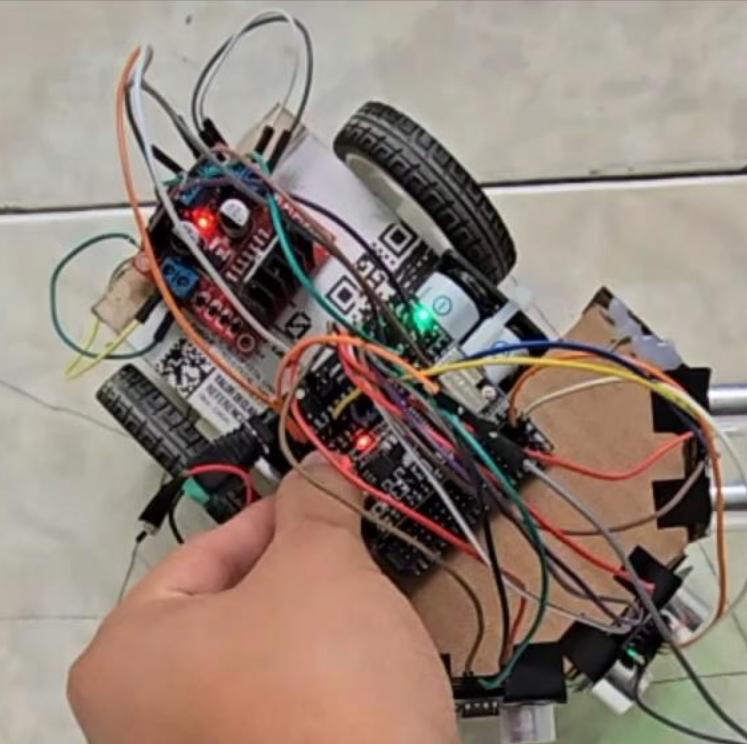


DESIGN AND CONSTRUCTION

Sim-to-Real Deployment Demo

- Real World Performance:
 - Success Rate: 80% (8/10 trials).
 - Inference Time: 32ms (Real-time capable).
 - RAM Usage: 11.5% (60KB used of 520KB).

Metric	Method A (Int8 Quantized)	Method B (Hybrid Float32)
Success Rate (n=10)	0%	80%
Avg. Inference Latency	~8 ms	~32 ms
Primary Failure Mode	Policy Collapse (Spinning)	Geometric Traps (Narrow Corners)
Model Size (Flash)	15 KB	60 KB
RAM Usage (Arena)	~4 KB	~60 KB



Conclusion & Future Work

- Conclusions:
 - Precision Matters: Int8 quantization destroys navigation policies.
 - Safety First: AI needs a deterministic safety wrapper.
 - Feasibility: ESP32 is capable of complex closed-loop control.
- Future Work:
 - Replace IR Goal Detector with ESP32-CAM (Computer Vision).
 - Train using PPO for continuous action space.