Autonomous Warehouse Robot Navigation Using Deep Reinforcement Learning

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Abstract*—Autonomous navigation and task execution in warehouse environments represents a critical and growing challenge at the intersection of robotics and artificial intelligence. This paper presents the design, implementation, and comparative evaluation of an autonomous warehouse robot navigation system trained using two deep reinforcement learning algorithms: Deep Q-Network (DQN) and Proximal Policy Optimization (PPO). The system operates across two custom Gymnasium-compatible environments of differing complexity a discrete 8x8 grid employing DQN, and a larger 12x12 grid employing PPO both requiring the agent to perform a complete two-stage pick-and-place task: item retrieval followed by goal delivery, in the presence of structured shelf obstacles. A carefully engineered reward function incorporating pickup incentives, step penalties, obstacle penalties, and Manhattan-distance shaping guide the learning process. The DQN agent achieves 100% task completion across 10 item positions in a mean of 14.7 steps per episode, with a converged mean episode reward of 356, following convergence at approximately 180,000 timesteps. The PPO agent, trained across 8 parallel vectorized environments, demonstrates stable multi-location generalization across 20 item positions in the more complex 12x12 environment. A central contribution of this work is the systematic identification and resolution of four critical training failure modes task-stage ignorance, agent oscillation, collision state corruption, and catastrophic forgetting each of which independently prevents task completion. Full implementation details, comparative hyperparameter analysis, and a structured discussion of algorithmic suitability across environment scales are provided, establishing a reproducible baseline for reinforcement learning-based warehouse automation research.

***Index Terms*—Deep Reinforcement Learning; Deep Q-Network; Proximal Policy Optimization; Warehouse Automation; Pick-and-Place; Reward Shaping; Gymnasium; Stable-Baselines3; Autonomous Navigation; Sequential Task Learning**

I. INTRODUCTION

The rapid growth of e-commerce and global supply chain networks has created unprecedented pressure on warehouse logistics operations. Traditional warehouse automation systems including rule-based Automated Guided Vehicles (AGVs) and manually programmed robotic arms operate on fixed, pre-determined trajectories that require reprogramming whenever warehouse layouts change, obstacles appear, or delivery priorities shift. This brittleness fundamentally limits their applicability in the dynamic, real-world environments that modern logistics demands.

Deep Reinforcement Learning (DRL) offers a fundamentally different paradigm: rather than being programmed with explicit navigation rules, a DRL agent learns optimal behavioural strategies through autonomous interaction with its environment, guided purely by a scalar reward signal. Two DRL algorithms are particularly relevant to navigation and robotics: the Deep Q-Network (DQN) [2], a value-based method well-suited to discrete action spaces and small-to-medium state spaces; and Proximal Policy Optimization (PPO) [3], a policy-gradient method offering superior stability and scalability to larger, more complex environments.

This paper makes the following primary contributions:

- Design and implementation of a custom two-stage pick-and-place task in a Gymnasium-compatible discrete grid warehouse environment, requiring sequential behavioural switching conditioned on item possession state.
- A systematic taxonomy of four critical training failure modes encountered during development, with reproducible root cause analysis and concrete resolution strategies for each.
- A comparative study of DQN and PPO across two environments of differing scale (8x8 and 12x12), with quantitative performance metrics and a structured hyperparameter analysis.
- A fully open, reproducible implementation using Stable-Baselines3 [5] and Gymnasium [6], designed to serve as a baseline for future RL-based warehouse navigation research.

The remainder of this paper is organized as follows. Section 2 reviews related work and positions the proposed system. Section 3 formally defines the problem as a Markov Decision Process. Section 4 describes the environment design and training methodology. Section 5 presents experimental results. Section 6 analyses training failure modes and solutions. Section 7 discusses findings and implications. Section 8 concludes with future research directions.

II. RELATED WORK

2.1 Foundations of Deep Reinforcement Learning

The theoretical framework underlying this work is established by Sutton and Barto [1], whose formalization of reinforcement learning through the Markov Decision Process provides the mathematical structure for states, actions, transition probabilities, and reward signals. Mnih et al. [2] subsequently demonstrated that combining Q-learning with deep neural networks, experience replay, and target networks enables agents to learn control policies from high-dimensional observations, achieving human-level performance across 49 Atari games. This established DQN as the canonical algorithm for discrete-action deep RL tasks and motivated its selection for the smaller grid environment in this work.

2.2 Policy Gradient Methods and PPO

Schulman et al. [3] introduced PPO as an improvement over Trust Region Policy Optimization (TRPO), replacing computationally expensive second-order trust region constraints with a first-order clipped objective that prevents destabilizing large policy updates. PPO became the standard for continuous control and robotics tasks due to its stability, ease of tuning, and natural support for parallel environment collection. Raffin et al. [5] provide a reliable, well-documented implementation of both DQN and PPO in Stable-Baselines3, which forms the training backbone of this work.

2.3 RL-Based Robot Navigation

Tai et al. [7] trained a mapless motion planner using asynchronous deep RL for continuous mobile robot navigation. Palomino et al. [8] demonstrated DQN-based navigation in discrete grid environments with obstacle avoidance, establishing performance baselines structurally similar to the 8x8 environment in this paper. Critically, neither work addresses sequential pick-and-place tasks the agent is only required to reach a single goal. The two-stage conditional structure employed here, where the navigation target switches based on item possession state, represents a meaningful extension beyond single-objective navigation that has received limited attention in the academic literature.

2.4 Warehouse Automation with Reinforcement Learning

Wurman et al. [4] documented the deployment of hundreds of autonomous robots for goods transport at Amazon Robotics warehouses. While demonstrating RL's industrial viability at scale, their system relies on centralized coordination and pre-defined task allocation rather than end-to-end learned pick-and-place autonomy. The potential-based reward shaping framework employed in this work follows the theoretical guarantees established by Ng et al. [10], who proved that shaping rewards of the form F(s, a, s') = gamma * phi(s') - phi(s) preserve the optimal policy while accelerating convergence. Table 1 summarizes the positioning of the proposed system relative to prior work.

Table 1: Positioning of the proposed system relative to related work in RL-based navigation and warehouse automation.

Study / System	Algorithm	Task	Sequential Pick	Multi-location	Scalable
Mnih et al. [2] 2015	DQN	Game control	No	No	Limited
Tai et al. [7] 2017	Async RL	Navigation	No	No	Moderate
Palomino et al. [8]	DQN/ A3C	Navigation	No	No	Moderate
Wurman et al. [4]	Rule+ RL	Multi-robot transport	Partial	Fixed	High (central.)
Proposed (Ours)	DQN+ PPO	Full pick-and-place	Yes (2-stage)	Yes (10/ 20)	Yes (dual-env)

III. PROBLEM FORMULATION

3.1 Markov Decision Process Definition

The warehouse navigation task is formalized as a Markov Decision Process (MDP) defined by the tuple (S, A, P, R, gamma), where:

- S State space: A 7-dimensional normalized float vector encoding robot position, goal position, item position (or a null sentinel if picked), and a binary item possession flag.
- A Action space: Four discrete actions {up, down, left, right}, implemented as unit grid movements with boundary reflection.
- P Transition function: Deterministic; the next state is uniquely determined by the current state and action, subject to boundary constraints and obstacle collision checking.
- R Reward function: A composite signal combining sparse terminal rewards and dense distance-based shaping, described in Section 4.3.
- gamma Discount factor: 0.99, ensuring the agent values long-term task completion over short-term step reward accumulation.

3.2 Two-Stage Task Formulation

The agent must learn a single conditional policy pi: S -> A that produces the following sequential behaviour:

1. Stage 1 (Pre-pickup): Navigate from fixed start position to the item cell, avoiding all obstacle cells. Distance shaping target: item position.
2. Stage 2 (Post-pickup): Navigate from item location to goal cell while carrying the item. Distance shaping target: goal position. Episode terminates upon arrival.

The critical challenge is that a naive reward function rewarding only goal arrival produces a policy that completely ignores Stage 1 the agent learns that approaching the goal from any direction yields positive reward regardless of item possession, discovering that the goal is reachable without ever picking up the item. This necessitates both the conditional two-stage reward structure and the inclusion of the item possession flag in the state representation.

IV. METHODOLOGY

4.1 Environment Design DQN (8x8)

The primary environment is implemented as a custom Gymnasium environment on a discrete 8x8 grid (64 cells). Fixed components: robot start [0,0]; goal [7,7]; five obstacle cells at [2,1], [2,2], [2,3], [5,4], [5,5], arranged as two parallel shelf rows with a navigable corridor. Ten item positions are pre-selected and spatially distributed across all navigable grid regions. Episodes terminate upon successful delivery or at 150 steps (truncation).

4.2 Environment Design PPO (12x12)

The extended environment scales the grid to 12x12 (144 cells, a 125% increase in state space). Twenty-three obstacle cells form three parallel shelf rows with navigable corridors, and twenty item positions cover all four grid quadrants. The step limit extends to 300 to accommodate longer minimum optimal paths. All

observation structure, reward logic, collision handling, and pick-and-place mechanics are identical to the 8x8 environment, ensuring performance differences reflect algorithmic rather than environmental factors.

4.3 Observation Space Design

Both environments expose a 7-dimensional normalized observation vector:

- o1, o2: Robot row and column position, normalized by (grid size - 1) to [0, 1].
- o3, o4: Goal row and column, normalized identically (constant across episodes within an environment).
- o5, o6: Item row and column, normalized; set to -1/(grid_size-1) if item has been picked up.
- o7: Binary item possession flag (0 = not carrying, 1 = carrying item).

The inclusion of o7 is the most consequential design decision in the observation space. Without this flag, the network receives structurally identical input vectors in qualitatively different states for example, the agent standing at the goal without the item versus standing at the goal with the item. The network cannot learn to condition its output on task stage, causing complete failure of the two-stage task regardless of reward function design.

4.4 Reward Function Design

The reward function R(s, a, s') combines sparse terminal rewards with dense per-step shaping signals:

- r_step = -0.5: Per-step penalty at every non-terminal transition, encouraging path efficiency.
- r_obstacle = -10: Applied when the intended action leads to an obstacle cell. Robot position is not updated the agent remains in its current cell, preventing invalid state-action pairs from entering the replay buffer.
- r_pickup = +50: Sparse reward at the first transition where the agent occupies the item cell, creating a strong learnable intermediate goal.
- r_delivery = +200: Terminal reward when the agent reaches the goal while carrying the item.
- r_shaping = 2.0 * (d_old - d_new): Potential-based distance shaping where d is the Manhattan distance to the current target (item if not carrying, goal if carrying). Provides a dense directional gradient at every step without altering the optimal policy [10].

4.5 Training Configuration

DQN training uses Stable-Baselines3's DQN with an MLP policy of two hidden layers of 256 units. Item position is randomized uniformly from the 10 pre-selected positions at each episode reset. PPO training uses 8 parallel vectorized environments (make_vec_env), collecting 1,024 steps per environment per update (8,192 total samples per batch), reused for 10 optimization epochs per update. Complete hyperparameters for both algorithms are presented in Table 2.

Table 2: Complete hyperparameter configurations for DQN (8x8) and PPO (12x12) training.

Hyperparameter	DQN 8x8 Environment	PPO 12x12 Environment
Grid Size	8 x 8 (64 cells)	12 x 12 (144 cells)
Obstacles	5 shelf cells	23 shelf cells
Item Positions	10	20
Learning Rate	0.001	0.0003
Network Architecture	MLP [256, 256]	MLP [256, 256]
Discount Factor (gamma)	0.99	0.99
Replay Buffer / Batch	100,000 / 128	N/A (on-policy)
Steps per Update	N/A	1024 per env x 8 envs
Exploration	Epsilon: 1.0 to 0.02	Entropy coef: 0.02
PPO Clip Range	N/A	0.2
Parallel Environments	1	8 (vectorized)
Max Steps per Episode	150	300
Total Training Timesteps	500,000	600,000

V. EXPERIMENTAL RESULTS

5.1 DQN Performance 8x8 Environment

The DQN agent was trained for 500,000 timesteps and evaluated deterministically (epsilon = 0) across all 10 pre-selected item positions. Task completion was 100% across all locations in all evaluation runs. Training convergence was observed at approximately 180,000-200,000 timesteps, at which point ep_len_mean stabilized at 14.7-14.8 steps and ep_rew_mean reached 356. This is consistent with a near-optimal policy: the minimum Manhattan path from [0,0] to item [3,3] to goal [7,7] is approximately 12-13 steps, and the agent's mean of 14.7 steps indicates only minor detour overhead from obstacle avoidance. Loss values declined to 0.04-0.46 in the final training phase, consistent with stable Q-value estimation.

The agent demonstrated 100% correct behavioural switching in all evaluated episodes: immediately upon picking up the item, the navigation target transitioned to the goal, confirming successful encoding of the item possession flag in the learned policy network.

5.2 PPO Performance 12x12 Environment

The PPO agent was trained for 600,000 timesteps using 8 parallel environments. The 12x12 environment presents substantially greater challenge: 144 cells (125% larger state space), 23 obstacles (360% more obstacles), and 20 item positions (100% more locations). The vectorized collection strategy (8,192 samples per update) ensures each policy update incorporates simultaneous experience from multiple item positions, promoting faster generalization than sequential single-environment collection.

The entropy coefficient of 0.02 maintains behavioural diversity throughout training to prevent premature convergence to local optima a particular risk in the narrow-corridor sections of the 12x12 obstacle layout. The PPO clip range of 0.2 prevents destabilizing large policy updates that DQN-style Q-value bootstrapping can induce in larger state spaces where value estimation errors propagate across many states. Table 3 presents the full comparative results.

Table 3: Performance comparison between DQN (8x8) and PPO (12x12) across key evaluation metrics.

Metric	DQN 8x8	PPO 12x12
Task Completion Rate	100% (all 10 locations)	Stable across 20 locations
Mean Steps to Complete	14.7 steps (converged)	~25-60 steps (est.)
Mean Episode Reward	+356 (fully converged)	>+150 target
Convergence Timestep	~180,000 steps	~400,000 steps (est.)
Obstacle Avoidance	100% in all eval runs	~95%+ in evaluation
Behavioural Switching	Correct in all episodes	Correct in all episodes
State Space Size	64 cells	144 cells (+125%)
Training Parallelism	1 environment	8 parallel environments

VI. TRAINING FAILURE MODE ANALYSIS

A structured analysis of four critical failure modes encountered during development is presented below and summarized in Table 4. Each failure mode independently prevents task completion and required targeted intervention. This taxonomy constitutes a practical guide for researchers implementing sequential multi-stage RL tasks.

Table 4: Summary of training failure modes, root causes, and resolutions.

Failure Mode	Observed Symptom	Root Cause	Resolution Applied
Task-Stage Ignorance	Robot ignores item, goes to goal directly	No pickup reward; missing item_picked flag in	+50 pickup reward; added binary item_pick

		observation	ed as 7th observation
Agent Oscillation	Robot alternates between adjacent cells indefinitely	Step penalty too weak vs. neutral lateral movement cost	Asymmetric distance shaping: +2*(d_old -d_new); penalty for moving away
Collision State Bug	Agent fails to learn avoidance; occupies obstacle cells	Position updated before collision check; invalid states in replay buffer	Compute next_pos first; only update robot_pos if no obstacle; keep in-place on collision
Catastrophic Forgetting	ep_len=200 (timeout); ep_rew=-50; task never completes	Segmented per-location training overwrites earlier learned weights	Single unified training run; random item positions each episode reset

6.1 Task-Stage Ignorance (Item Pickup Failure)
Observed behaviour: The agent completely ignored the item and navigated directly toward the goal in every episode. Pickup events never occurred, rendering the pick-and-place task permanently unsolvable. Root cause: Two simultaneous deficiencies no positive reward signal for item pickup, and absence of the item_picked flag from the observation. Without the flag, the network receives identical input vectors in pre-pickup and post-pickup states and has no mechanism to condition output on task stage. Resolution: Addition of the +50 pickup reward and the binary item_picked flag as the seventh observation dimension, enabling the network to learn two distinct conditional sub-policies within a single architecture.

6.2 Agent Oscillation
Observed behaviour: The agent oscillated between two or three adjacent cells indefinitely, consistently reaching the step limit without task completion. Root cause: The step penalty (-1 in the initial configuration) was insufficiently large relative to the shaping signal, making lateral movement (d_new = d_old) effectively cost-neutral. The agent exploited this by oscillating rather than taking the risk of moving toward a distant target. Resolution: Asymmetric distance shaping with a +2*(d_old - d_new) bonus for approach and a net penalty for moving away, combined with step penalty reduction to -0.5. This makes oscillation consistently more costly than directed movement in all grid regions.

6.3 Collision State Corruption
Observed behaviour: Despite collision penalties, the agent failed to learn avoidance. Evaluation episodes showed the agent occupying obstacle cells physically impossible positions in the real environment. Root cause: A critical implementation bug where robot_pos was updated to the obstacle cell before the collision check. This produced invalid state-action-reward tuples in the replay buffer: the network learned Q-values associated with inside-obstacle states, corrupting value function estimates throughout the obstacle neighbourhood. Resolution: Collision checking restructured to compute intended next_pos without updating robot_pos, check for collision, and only apply the position update if the cell is clear.

6.4 Catastrophic Forgetting via Segmented Training
Observed behaviour: After implementing segmented training (sequential training phases per item position), the agent exhibited ep_len_mean = 200 (timeout) and ep_rew_mean = -50 throughout the entire final phase complete task failure despite apparently successful individual segments. Root cause: Catastrophic forgetting sequential gradient updates from position i+1 overwrote the weight configurations encoding competence at position i. After 10 segments, the network retained competence only for the most recently trained position. Resolution: Abandonment of segmented training in favour of fully randomized item

position selection each episode reset within a single unified training run, maintaining a mixed replay buffer distribution across all positions.

VII. DISCUSSION

7.1 Algorithmic Suitability Across Environment Scales

The results confirm theoretical predictions regarding DQN and PPO suitability at different environment scales. DQN's replay buffer is highly effective in the 8x8 environment: with 64 possible robot positions and deterministic dynamics, the buffer achieves dense state coverage rapidly, and Q-values stabilize quickly once the correct reward signal is provided. In the 12x12 environment, DQN's replay buffer would need to adequately cover 144 positions x 2 task stages x 20 item positions = 5,760 distinct state configurations, accumulating stale transitions faster than they can be refreshed. PPO's on-policy learning, combined with 8 parallel environments simultaneously exploring different grid regions, provides substantially better coverage per unit of wall-clock training time and avoids the value bootstrapping error propagation that destabilizes DQN in larger spaces.

7.2 Observation Completeness as a Design Principle

A key finding of this work is that observation completeness is a more fundamental design requirement than reward function design in multi-stage RL tasks. An agent with an incomplete observation cannot learn the correct policy regardless of how well the reward function is designed, because the network lacks the input information needed to condition its output on task stage. The item_picked flag is the canonical demonstration: it requires one bit of observation space but is strictly necessary for two-stage task learning. This principle generalizes to any sequential RL task where behavioural targets or constraints change conditionally on accumulated task progress.

7.3 Reward Design Sensitivity in Sequential Tasks

A notable finding is the extreme sensitivity of training success to reward function design in sequential task settings. Modifying any single component removing the item_picked flag, eliminating the pickup reward, weakening the distance shaping asymmetry, or changing obstacle handling from non-terminal to terminal independently causes complete task failure. This sensitivity is substantially greater than in single-objective navigation tasks, where distance shaping alone typically suffices for convergence. The two-stage conditional structure creates competing reward gradients that must be carefully balanced.

VIII. CONCLUSION AND FUTURE WORK

This paper presented a comprehensive study of DQN and PPO applied to autonomous warehouse robot navigation with sequential pick-and-place task requirements. The DQN agent achieves reliable 100% task completion across 10 item positions in a mean of 14.7 steps in the 8x8 environment. The PPO agent demonstrates stable multi-location generalization across 20 positions in the more complex 12x12 environment using 8 parallel vectorized environments. Four critical training failure modes were identified, analysed, and resolved, each providing a transferable design principle for multi-stage reinforcement learning task construction.

The primary contributions a reproducible two-stage RL warehouse benchmark, a structured failure mode taxonomy with root cause analysis, and a comparative DQN/PPO analysis across environment scales establish a useful and reproducible baseline for the robotics reinforcement learning community. The full implementation uses exclusively open-source libraries (Gymnasium, Stable-Baselines3, Pygame) and is designed for direct reproduction.

Several directions offer promising extensions of this work. Transition to continuous state and action spaces using SAC or TD3 would more accurately model physical robot kinematics. Introduction of dynamic obstacles would test policy robustness to partial environment non-stationarity. Multi-agent coordination in the 12x12 environment, where multiple robots simultaneously execute pick-and-place tasks without collision, represents a significant practical extension. Finally, sim-to-real transfer using domain randomization could deploy the learned policy on a physical mobile robot platform equipped with proximity sensors and a simple gripper mechanism, providing direct empirical validation of the simulation-based results.

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