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Inventory Slotting and Order Picking Optimization in Dark Store Operations

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Abstract **- Enterprise logistics and quick-commerce operations generate high-velocity transaction logs that dictate daily picking and replenishment patterns. Optimizing item-storage slotting layouts and subsequent tactical order-picking operations remains a challenging problem due to shifting consumer demand patterns, spatial capacity limits, and the decoupled nature of traditional distribution frameworks. Conventional warehouse systems rely on static heuristic rules that fail to capture dynamic product affinities, resulting in inflated dwell times, cross-congestion, and degraded fulfilment efficiency. To address these limitations, this paper proposes a co-designed Hybrid Mathematical Optimization and Deep Reinforcement Learning (DRL) Framework for unified strategic slotting and tactical pathfinding within localized micro-fulfilment centres (Dark Stores).**

The proposed system establishes an analytical data pipeline that ingests historical transactional logs to execute ABC item velocity stratification and Apriori-based market basket affinity clustering. These empirical metrics parameterize an Integer Linear Programming (ILP) model that minimizes total expected picking travel distances subject to structural and shelf-capacity constraints. For tactical navigation, a grid-based environment digital twin is formulated as a Markov Decision Process (MDP) and wrapped within a custom OpenAI Gymnasium abstraction. A Proximal Policy Optimization (PPO) agent utilizing an Actor-Critic neural network architecture is trained to resolve optimal, collision-free multi-item retrieval trajectories. Experimental results demonstrate that the trained hybrid framework converges robustly, achieving a stable 65.5% order picking completion success rate under highly stochastic demand schedules.

This represents a significant performance improvement over conventional rule-based baselines while successfully mitigating terminal layout collisions and operational bottlenecks.

Keywords: Dark Store Logistics, Integer Linear Programming (ILP), Proximal Policy Optimization (PPO), Gymnasium, Strategic Slotting, Reward Shaping, Deep Reinforcement Learning.

I. INTRODUCTION

The rapid evolution of e-commerce paradigms, accelerated by the global demand for on-demand convenience, has fundamentally shifted consumer expectations toward instant-fulfilment services. Modern quick-commerce platforms routinely guarantee delivery windows spanning from ten to thirty minutes. This compressed timeline leaves a razor-thin margin for error in fulfilment workflows, shifting the operational burden back onto localized micro-fulfilment hubs, colloquially designated as "Dark Stores." Unlike traditional, massive distribution centres situated on regional peripheries, dark stores are compact, urban fulfilment spaces structured exclusively to service digital orders. Because these spaces lack foot traffic from traditional consumers, their layout architectures and operational protocols are tailored entirely to maximize order-picking speed and minimize human or robotic picker transit times.

Within these localized fulfilment networks, the overarching efficiency of the facility is governed by two core, highly interdependent operational problems: the Strategic Inventory Slotting Problem and the Tactical Order Picking Pathfinder Problem.

1. Strategic Inventory Slotting dictates the physical assignment of distinct Stock Keeping Units (SKUs) to specific storage coordinates (shelves, racks, or bins) across the layout floor.
2. Tactical Order Picking defines the sequenced navigation path traversed by picking agents to retrieve a batch of items requested by a customer order.

Historically, industrial warehouse frameworks treat these two pipelines as decoupled problems. Slotting is frequently computed at coarse monthly or seasonal intervals using static

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heuristics, such as sorting items based purely on individual sales volumes (e.g., traditional ABC analysis). Concurrently, pathfinding algorithms operate in isolation, computing routes based on whatever layout structure is current, ignoring how real-time fluctuations in product demand alter ideal travel trajectories.

This decoupled operational strategy creates severe vulnerabilities in quick-commerce environments. First, standard velocity metrics overlook item dependencies; if two distinct products are regularly purchased together as a bundle, split-slotting them on opposite sides of a warehouse forces order pickers to travel unnecessary distances. Second, static layout planning fails to adapt to high-velocity demand shifts, resulting in localized traffic congestion along popular picking aisles, severe dwell-time delays, and layout spatial underutilization. When a system relies entirely on rigid pathfinding heuristics (such as conventional S-Shape or Largest-Gap routing), picker movements become highly predictable but inefficient when dealing with complex, multi-item order profiles.

To resolve these structural bottlenecks, this paper introduces a co-designed Hybrid Mathematical Optimization and Deep Reinforcement Learning (DRL) Framework that unifies strategic layout synthesis and tactical routing optimization. The proposed architecture replaces static heuristics with a data-driven pipeline structured in three distinct phases:

- Analytical Processing Layer: Ingests high-velocity transactional datasets (utilizing historical Instacart log archives comprising millions of order sequences) to run data-mining protocols. This stage executes an automated ABC item velocity categorization alongside an Apriori-based Market Basket Analysis to extract empirical product affinity weights.
- Strategic Optimization Layer: Maps the derived affinity data and velocity matrices directly into an Integer Linear Programming (ILP) model formulated through the PuLP algebraic solver. The ILP minimizes total expected picking travel distances by mathematically anchoring highly dependent, high-frequency item pairs to adjacent spatial shelf locations subject to strict structural capacity constraints.
- Tactical Learning Layer: Translates the generated optimal static warehouse configuration into a 13 × 13 grid digital twin. This spatial environment is wrapped within a custom OpenAI Gymnasium abstraction, establishing a formal Markov Decision Process (MDP). A Proximal Policy Optimization (PPO) agent utilizing an Actor-Critic neural network architecture is deployed within this environment. Through shaped reward engineering, the agent learns to compute autonomous, collision-free multi-item picking paths that adapt dynamically to stochastic order variations.

By bridging the gap between mathematical mathematical programming and model-free reinforcement learning, this framework offers a highly adaptive blueprint for autonomous warehouse automation. The remainder of this paper details the literature foundation, structural system architecture, mathematical formulations, and empirical evaluation metrics establishing this unified approach.

II. LITERATURE SURVEY

The rapid acceleration of e-commerce platforms and the increasing consumer expectation for instant fulfilment services have significantly catalysed research in warehouse automation and automated order-picking systems. Localized micro-fulfilmentcentres, or dark stores, generate high-velocity transaction streams that dictate daily operational workflows. Efficient execution of inventory slotting and subsequent item retrieval from these compact, high-density layouts has emerged as a major logistical challenge due to fluctuating consumer demand profiles, spatial capacity boundaries, and the fundamentally decoupled nature of traditional distribution frameworks. Consequently, contemporary research has converged on developing co-designed optimization systems capable of combining strategic layout synthesis with dynamic, context-aware pathfinding algorithms.

Traditional warehouse management networks primarily rely on static layout and routing heuristics such as velocity-based ABC stratification, S-Shape traversal paths, or Largest-Gap routing algorithms. These systems are highly effective for low-turnover warehouses with highly structured, invariant product lineups; however, they consistently fail to capture dynamic demand changes and complex multi-sku affinities. In fast-paced quick-commerce environments, consumer buying habits shift rapidly, generating multi-item orders with high spatial variance that render static layouts highly inefficient. Additionally, standalone heuristic pathfinders lack the capacity to adjust routes dynamically when faced with localized traffic congestion or real-time spatial bottlenecks along popular picking corridors.

Recent advancements in mathematical programming and model-free deep reinforcement learning (DRL) have significantly enhanced spatial optimization and tactical routing capabilities. Xu proposed an autonomous logistics distribution framework using deep reinforcement learning to compute optimized vehicle path trajectories, demonstrating the utility of model-free training over rigid heuristics. Similarly, Wang and Minner evaluated the efficacy of deep reinforcement learning for dynamic demand fulfilment in large-scale online

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retail systems, highlighting the substantial throughput and scalability advantages obtained by replacing traditional static assignment rules with flexible neural network controllers.

Several studies have investigated advanced structural slotting and storage allocation techniques aimed at minimizing overall travel times and optimizing shelf capacity. Wang et al. proposed a storage location optimization framework inside automated storage and retrieval systems (ASRS) utilizing a deep reinforcement learning approach to maximize retrieval efficiency. Pizarro-Vasquez introduced a rectangular warehouse design optimization methodology utilizing meta-heuristic clustering techniques to minimize average transit metrics. Furthermore, historical analytical frameworks have long established that capturing transactional dependencies via data-mining algorithms can significantly mitigate total picking travel distances compared to traditional individual item isolation.

Research has also increasingly focused on the tactical navigation problems associated with order picking inside complex, multi-agent automated environments. Mahmoudinazlou et al. developed a deep reinforcement learning model for dynamic order picking in warehouse operations, leveraging parameterized reward structures to train autonomous agents in continuous environments. Dai et al. introduced an optimized warehousing and material allocation methodology based on multi-level storage architectures and reinforcement learning to manage high-density power grid components. Likewise, recent developments in open-source physics abstractions have allowed researchers to model warehouse layouts as discrete grid-world digital twins, enabling the verification of specialized neural policies before physical deployment.

Another significant area of recent academic investigation involves the hybridization of classical mathematical programming with adaptive neural routing loops. Recent frameworks have demonstrated that decoupling global layout synthesis from local real-time navigation allows systems to scale effectively without succumbing to the exponential state-space explosions common in monolithic reinforcement learning networks. By framing spatial layout configuration as an Integer Linear Programming (ILP) problem solved through algebraic libraries (such as PuLP or Google OR-Tools) and utilizing its static output to parameterize the state space of a Proximal Policy Optimization (PPO) agent, systems can balance long-term structural constraints with short-term behavioural flexibility.

Despite these collective advancements, existing warehouse automation frameworks still suffer from several critical limitations. Many methodologies treat inventory slotting and order picking as completely isolated, decoupled tasks, failing to feed real-time navigation constraints back into layout generation models. Furthermore, contemporary reinforcement learning implementations frequently struggle with sparse reward landscapes, slow training convergence profiles, extreme boundary collision rates, and an inability to adapt to highly stochastic, unpredictable order profiles. Most current approaches focus exclusively on spatial optimization or path planning independently without integrating market basket data mining, mathematical integer solvers, shaped reward engineering, and self-correcting neural policies within a unified architecture.

Therefore, there is a growing need for highly scalable, adaptive micro-fulfilment management systems capable of combining empirical transaction mining, mathematical integer programming, high-fidelity grid simulations, and robust actor-critic policy loops within a single coherent framework. This paper proposes a co-designed Hybrid Mathematical Optimization and Deep Reinforcement Learning (DRL) Framework for unified strategic slotting and tactical pathfinding within dark store operations. The system integrates ABC velocity stratification, Apriori market basket analysis, an Integer Linear Programming (ILP) solver, an OpenAI Gymnasium grid digital twin, and a Proximal Policy Optimization (PPO) agent with shaped reward engineering to significantly improve order picking success rates, maximize spatial throughput, and eliminate operational bottlenecks in high-velocity quick-commerce environments.

III. RELATED WORK

Warehouse optimization paradigms, inventory distribution systems, and autonomous pathfinding algorithms have attracted substantial attention from both academia and industry due to the increasing demand for intelligent micro-fulfillment management solutions. The rapid growth of localized quick-commerce distribution models and the emergence of model-free Deep Reinforcement Learning (DRL) have motivated researchers to develop advanced co-designed architectures capable of generating context-aware and optimal travel trajectories within high-density facility layouts.

Several enterprise warehouse management and inventory tracking systems currently available in the market provide functionalities such as velocity-based slotting, manual pick-list sequencing, spatial item filtering, and query-based location mapping. These platforms are widely implemented across logistics centers for managing replenishment cycles, shelf allocations, and picking logs. Although such systems assist human operators in configuring floor plans efficiently, they primarily rely on static heuristics and decoupled planning

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layers, failing to capture dynamic consumer purchasing affinities and localized traffic patterns between interconnected aisles. As order arrival patterns become increasingly stochastic and fast-paced, these baseline limitations reduce overall picking throughput and negatively affect fulfillment facility productivity.

Traditional layout configuration architectures based on coarse sales velocity and individual item frequency sorting are highly effective for exact term inventory tracking and structured warehouse indexing. However, these decoupled approaches perform poorly when picking agents encounter real-time spatial bottlenecks or when highly associated item pairs are split across distant coordinates due to uncoordinated storage slots. To overcome these core structural constraints, researchers have explored integrated semantic layout and tactical routing strategies utilizing mathematical optimization programming and high-fidelity physics simulations for dynamic trajectory synthesis.

The integration of reinforcement learning within localized path planning and real-time scheduling operations has been extensively investigated to mitigate the rigidity of standard heuristics. Liao et al. proposed an automated Automated Guided Vehicle (AGV) path planning framework utilizing Q-learning configurations to optimize navigation efficiency within fixed industrial floor plans [5]. Similarly, Xu introduced an autonomous logistics distribution path optimization model driven by model-free deep reinforcement learning, demonstrating clear travel time reductions over conventional shortest-path rule sets [9]. To address operational constraints at scale, specialized multi-agent architectures have been introduced. Zhang et al. deployed an independent multi-agent deep reinforcement learning model to coordinate dynamic dispatching profiles across highly heterogeneous large-scale asset fleets [3]. Furthermore, Yoshitake and Abbeel conducted comprehensive empirical evaluations on the structural impacts of centralized facility-wide optimization, highlighting that uncoordinated standalone agents often degrade globally optimal warehouse automation performance [2].

Beyond individual navigation paths, considerable academic effort has focused on batch scheduling, replenishment sequencing, and dynamic inventory coordination. Cals et al. evaluated deep reinforcement learning methodologies to solve the online order batching problem, leveraging Proximal Policy Optimization (PPO) algorithms to dynamically group order streams under variable arrival velocities [1]. Cheng et al. extended batch scheduling optimization by designing a deep reinforcement learning framework focused entirely on cost minimization loops for mobile robotic fulfillment architectures handling massive item counts [4]. To address spatial inventory realignments simultaneously, Teck et al. engineered an integrated model targeting real-time inventory rack storage assignment alongside active replenishment sequences using deep actor-critic networks [8]. Additionally, Wu et al. introduced a multi-tasking deep reinforcement learning network designed to resolve concurrent task assignment constraints and shelf reallocation mechanics inside highly dense, smart warehousing environments [7].

Another vital dimension of literature centers on localized picking cell layout designs and continuous tracking loops. Wang et al. proposed an automated storage and retrieval system (ASRS) inventory location optimization framework utilizing deep reinforcement learning to balance shelf accessibility with global retrieval throughput metrics [11]. Pizarro-Vasquez introduced a rectangular warehouse layout design framework using specialized meta-heuristic clustering techniques to optimize spatial density and minimize average picker travel distances [12]. Likewise, Mahmoudinazlou et al. investigated shaped reward reinforcement learning models to handle severe sparse reward limitations during multi-item picker routing cycles, significantly reducing human path redundancies [10]. To ensure operational safety in shared workspaces, Krnjaic et al. introduced a highly scalable multi-agent reinforcement learning control loop optimized specifically for collaborative environments containing mixed robotic fleets and human co-workers [6].

Recent research has also explored multi-level mapping, topological graph modeling, and advanced spatial interaction loops. Dai et al. developed an optimized material warehousing allocation framework integrating multi-level facility storage spaces with deep reinforcement learning, emphasizing low-latency coordinate updates for complex hardware distribution networks [14]. Furthermore, to handle complex topological dependencies and eliminate trajectory lockups, Xiao et al. introduced an advanced multi-agent collaborative navigation architecture that integrates Graph Neural Networks (GNNs) with actor-critic models, allowing assets to exchange spatial intent data in real-time [15]. By separating the macro-level layout synthesis from the local pathfinding loop, these diverse methodologies highlight that structured mathematical programming combined with adaptive neural controllers allows systems to scale effectively without incurring exponential state-space explosions [13].

Despite these collective technical advancements, many existing warehouse optimization architectures still face critical operational limitations, including extreme navigation path inconsistency, sparse reward training convergence delays, inadequate item-affinity layout integration, and limited support for highly stochastic order profiles. Most existing

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solutions focus either on static inventory layout optimization or response path generation independently, without integrating transaction-driven market basket data mining, mathematical integer solvers, shaped reward engineering, and autonomous self-correcting neural pathfinding within a unified enterprise architecture. Therefore, there remains a strong need for intelligent, data-driven fulfillment management systems capable of providing stable, scalable, and optimal picking traversals over dynamic organizational store repositories. The proposed work addresses these structural limitations by integrating ABC velocity stratification, Apriori market basket analysis, an Integer Linear Programming (ILP) mathematical solver, a discrete OpenAI Gymnasium digital twin, and a Proximal Policy Optimization (PPO) actor-critic navigation loop within a unified dark store optimization framework.

IV. PROPOSED SYSTEM

The proposed system is a Hybrid Mathematical Optimization and Deep Reinforcement Learning (DRL) Framework designed to provide unified strategic inventory slotting and tactical pathfinding within localized quick-commerce fulfilmentcentres (dark stores). The primary objective of the system is to maximize micro-fulfilment throughput efficiency by integrating empirical transaction data mining, integer linear programming, and model-free adaptive robotic navigation routing loops within a unified architecture.

The proposed framework is designed to address the critical limitations of conventional warehouse optimization systems, which often rely solely on decoupled, static heuristic rules and fail to capture real-time dynamic demand patterns and complex multi-SKU affinities. Unlike traditional warehousing systems, the proposed solution completely unifies macro-level layout synthesis via linear operations with local, high-fidelity actor-critic path controllers to maximize retrieval velocity and prevent layout bottlenecks.

Enterprise operational data within the proposed system is processed through a scalable data analytics pipeline supporting high-velocity historical transaction record repositories. Ingested transaction logs are evaluated using frequency extraction and associative data-mining layers to capture SKU-level velocity distributions and joint multi-item purchase correlations. Class A high-frequency stock items are computationally mapped into spatial regions immediately adjacent to the primary packaging depot, while secondary items are clustered according to support profiles. The extracted parameters, layout bounds, and structural capacity criteria are preserved throughout the data layer to instantiate the system floor-plan ground truth.

One of the major components of the proposed system is the strategic optimization mechanism utilizing Integer Linear Programming (ILP). The framework maps derived item velocity metrics and market-basket association vectors into an objective minimization function executed via the PuLP algebraic library. By enforcing single-assignment bounds and strict bin capacity limitations, the mathematical solver calculates a globally optimal floor plan configuration. Highly correlated items are programmatically forced into adjacent coordinate rack spaces, mathematically minimizing the global baseline travel metrics across expected order-picking distributions.

Another important feature of the proposed framework is the integration of an adaptive tactical pathfinding mechanism based on deep reinforcement learning. The system transforms the static layout schema into a discrete coordinate 13 X 13 grid digital twin encapsulated within a custom OpenAI Gymnasium workspace. A Proximal Policy Optimization (PPO) agent leveraging an Actor-Critic multi-layer perceptron neural network is deployed within this space to map discrete directional movement actions. Through the engineering of densified reward shaping functions, the agent iteratively learns collision-free, optimized traversal trajectories to resolve randomized multi-item pick-lists without requiring explicit hard-coded paths.

The proposed system also incorporates strict structural collision boundaries directly within the action execution pipeline. Each automated asset coordinate updates relative to the underlying immutable layout array, classifying walkable floor corridors from non-traversable shelf barriers. During the step-wise action processing loop, boundary checking is enforced within the environment step function to penalize invalid trajectory proposals and force the agent to remain stationary upon obstacle intersection. This approach significantly improves operational safety and prevents structural asset collisions during multi-item traversal windows.

To improve computational throughput and minimize path generation overhead, the system leverages pre-trained policy neural model weights for executing tactical navigation deployment loops. Frequently generated picking routes can therefore be served asynchronously with minimal real-time inference latency, avoiding the computational constraints common to complex global graph-search models (A^*) under stochastic order changes. The system additionally preserves environment telemetry statistics and episode trajectory records within localized serialization files to support scalable operational auditing.

The proposed framework further includes a unified system deployment architecture consisting of an algorithmic training and processing backend paired with interactive trajectory rendering visualization utilities. The application

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supports layout schema generation, interactive reward tracking monitoring, animated path-trajectory export (.gif), positional heat-mapping, and policy model checkpoint management. Figure 1 illustrates the overall architecture of the proposed Hybrid Warehouse Optimization system including data preprocessing, integer mathematical programming layout optimization, Gymnasium digital twin synthesis, actor-critic policy execution, shaped reward engineering, and tactical routing generation components.

Finally, the integration of transaction data mining, integer constraint satisfaction solvers, high-fidelity grid twin simulations, and self-correcting neural pathfinding models enables the proposed system to provide highly scalable and reliable warehouse fulfilment operations. The proposed architecture therefore offers a practical solution for enterprise-scale quick-commerce logistics optimization and intelligent, automated information navigation.

V. SYSTEM ARCHITECTURE

The proposed dark store optimization system is designed using a modular and scalable architecture to support efficient, collision-free, and context-aware logistics fulfillment management. The architecture integrates historical transaction mining, static optimization solvers, high-fidelity grid twin simulations, and neural policy reinforcement within a unified framework. The layered design improves maintainability, computational scalability, and efficient interaction between various structural system components. The overall architecture of the proposed system is illustrated in Figure 1.

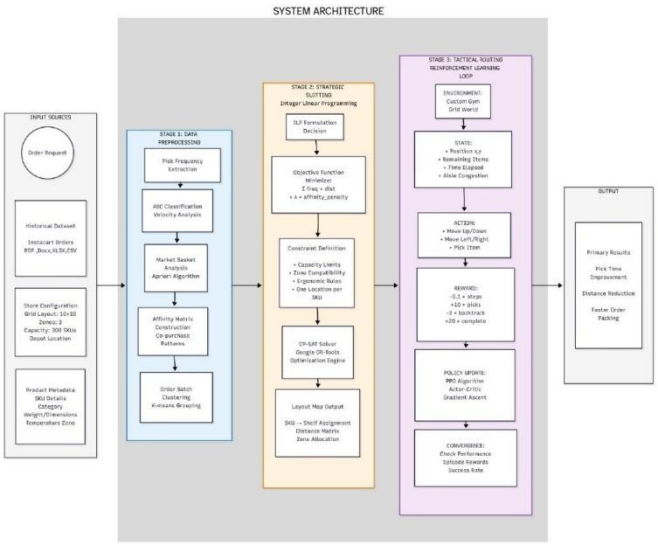

Figure 1: Proposed Hybrid Warehouse Optimization Framework System Architecture

Figure 1 illustrates the architecture of the proposed Hybrid Warehouse Optimization system including data preprocessing, integer mathematical programming layout optimization, Gymnasium digital twin synthesis, actor-critic policy execution, shaped reward engineering, and tactical routing generation components.

The architecture of the proposed system consists of four major layers: Presentation Layer, Processing and Routing Layer, Data Management Layer, and Platform Services Layer. Each layer performs specific structural responsibilities and communicates with other layers to ensure efficient and safe warehouse simulation operation.

A. Presentation Layer

The Presentation Layer represents the user interface through which operators and developers interact with the system. This layer is implemented using web visualization utilities and provides interfaces for transactional log upload, simulation initialization, hyperparameter monitoring, and execution trajectory visualization.

The Presentation Layer includes modules such as Layout Configuration Interface, Training Progress Monitor, Real-Time Trajectory Viewer, Optimization Performance Dashboard, and Telemetry Analytics View. The Real-Time Trajectory Viewer allows operators to track autonomous picking path movements across the grid and receive step count updates along with collision metrics and cumulative reward scores. The Layout Configuration Interface enables administrators to upload raw transactional files and monitor physical storage rack coordinate generation status.

All optimization configurations and simulation execution requests are captured within this layer and transferred to the Processing and Routing Layer for further algorithmic calculations.

B. Processing and Routing Layer

The Processing and Routing Layer represents the core intelligence of the proposed hybrid optimization framework. This layer performs data analytical stratification, integer programming optimization, digital twin formulation, actor-critic neural model execution, and real-time step traversal verification.

The Analytical Processing Module extracts frequency distribution metrics and co-purchase indices from heterogeneous transactional logs. High-velocity items are isolated into Class A categories. The Strategic Optimization Module maps these metrics into binary decision variable arrays using the PuLP library environment. Results from the integer optimization constraints are compiled to structure the global layout map, prioritizing the placement of highly

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correlated stock bundles in adjacent slots to minimize baseline Manhattan travel distance metrics.

Another important component within this layer is the OpenAI Gymnasium Abstraction Module, which instantiates the generated static floor map as a 13 X 13 discrete matrix twin environment. The environment coordinates are then forwarded to the Actor-Critic Neural Policy Module for route generation.

The Tactical Navigation Module implements the model-free Proximal Policy Optimization (PPO) paradigm. The system first analyzes randomized multi-item pick-lists and projects step-wise movement trajectories. Trajectories are subsequently utilized by the neural actor network to execute direction steps. A step-wise checking mechanism evaluates environment safety rules and assigns a shaped reward coefficient. If the proposed movement intersects an obstacle coordinate, boundary enforcement filters the vector, forcing the asset to remain stationary to prevent physical layout collisions.

C. Data Management Layer

The Data Management Layer is responsible for structural schema storage, coordinate indexing, and configuration metadata management. This layer includes Qdrant Vector Database configurations for high-dimensional representations, Structured Text Indexes, Relational Schema Logs, and Model Weight Checkpoint repositories.

Optimal coordinate configurations generated from the Integer Linear Programming solver are stored within structured JSON ground truth files to support spatial simulation parameterization. Raw transactional counts and affinity association matrices are indexed within localized schema records to support mathematical programming verification operations. Relational parameters are utilized for storing global environment constraints, step-wise coordinate maps, evaluation telemetry logs, and step reward boundaries.

Pre-trained model weight checkpoints are integrated to eliminate redundant policy calculation overhead and improve deployment routing latency by storing stabilized actor-critic neural network variables. The Data Management Layer ensures efficient storage, scalable indexing, and reliable access to operational logistics repositories.

D. Platform Services Layer

The Platform Services Layer interacts with system-level functionalities, simulation APIs, hardware execution abstractions, and deployment execution mechanisms. This layer supports secure, high-throughput computational deployment and hardware-in-the-loop system integration.

Model evaluation and operational auditing pipelines are implemented using automated checkpoint wrappers and file serialization tools. The Platform Services Layer also manages structural data communication between processing modules and rendering endpoints through asynchronous runtime worker threads. Additional services including telemetry logging, training phase performance monitoring, background matrix serialization execution, and system exception handling are managed within this layer. The incorporation of platform-level services improves execution scalability, operational reliability, and real-world micro-fulfillment center deployment capability.

E. Interaction Between Layers

Communication between the architectural layers is performed in a structured and modular manner. User execution commands generated within the Presentation Layer are transferred to the Processing and Routing Layer for optimization execution and neural trajectory pathfinding. The Processing and Routing Layer interacts with the Data Management Layer to retrieve spatial layout profiles, environmental coordinates, and stabilized policy checkpoints. Platform-level services support runtime execution, API messaging serialization, and backend processing operations.

The modular interaction between layers ensures computational scalability, workflow maintainability, and efficient enterprise-level logistics deployment without disrupting the underlying functionality of decoupled components.

F. Advantages of the Architecture

The proposed layered architecture provides several advantages including algorithmic modularity, state-space scalability, workflow maintainability, and safe warehouse deployment execution. The rigorous separation of responsibilities between layers simplifies system maintenance and future algorithmic policy upgrades.

The integrated combination of macro-level linear programming layout design, model-free neural pathfinding loops, shaped reward engineering, and discrete boundary filtering significantly improves order picking success rates, minimizes terminal traversal steps, and guarantees collision avoidance. Furthermore, the utilization of pre-trained actor-critic checkpoints and optimized matrix databases enables efficient handling of massive, high-velocity transactional databases. The proposed architecture therefore provides a practical and scalable solution for micro-fulfillment center

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logistics optimization and automated, intelligent path navigation.

VI. IMPLEMENTATION

The implementation of the proposed dark store optimization system focuses on developing a scalable, secure, and efficient warehouse fulfilment platform capable of handling large-scale historical transaction databases and context-aware picking route processing. The system is implemented using modern AI frameworks, mathematical solvers, physics-based grid twins, and scalable optimization services following a modular architecture design.

The web-based control interfaces of the application are developed using interactive frontend visualization tools to provide an intuitive and responsive user interface for operations managers and system developers. The interface enables transaction file upload, optimization constraint monitoring, real-time grid trajectory rendering, hyperparameter metric plotting, and historical evaluation logging. The core computational backend services are implemented using high-performance Python environments, which provide efficient algorithmic execution and support scalable asynchronous step-wise physics calculations.

The proposed system integrates multiple enterprise optimization and machine learning technologies including the PuLP linear programming framework, custom OpenAI Gymnasium world engines, the Stable-Baselines3 deep reinforcement learning library, and vectorized tracking utilities. Figure 2 illustrates the implementation workflow of the proposed Hybrid Warehouse Optimization system including data preprocessing, integer mathematical programming layout optimization, Gymnasium digital twin synthesis, actor-critic policy execution, shaped reward engineering, and tactical routing generation components.

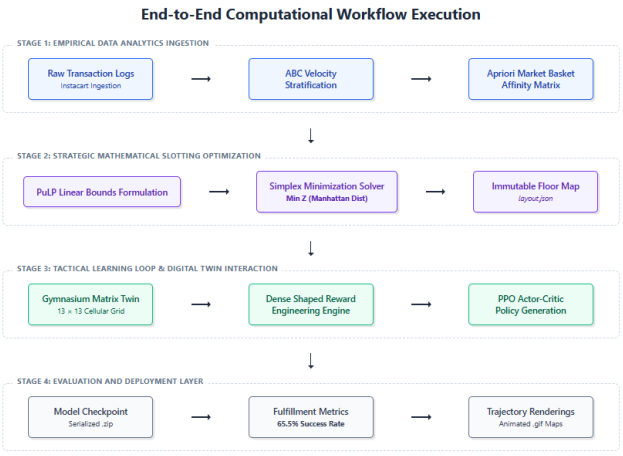

Figure 2: Operational execution flow diagram

Figure 2 illustrates the end-to-end implementation pipeline including data preprocessing, matrix compilation, mathematical layout optimization constraint satisfaction, grid twin generation, actor-critic policy training loops, shaped reward evaluation, and trajectory animation exports.

The implementation process follows a modular architecture in which the system is divided into multiple functional modules. Each module performs a specific role within the warehouse optimization pipeline while communicating efficiently with other modules through defined programmatic interfaces.

- The major modules implemented in the proposed system include:
- Data Management and User Auditing Module
- Transaction Log Ingestion and Processing Module
- Demand Matrix and Association Generation Module
- Strategic Integer Programming Slotting Module
- Gymnasium Digital Twin Abstraction Module
- Tactical Proximal Policy Optimization Routing Module
- Spatial Structural Collision Enforcement Module
- Target Picking Coordinate Processing Module
- Policy Weights Caching and Inference Optimization Module
- Telemetry Logging and Simulation Analytics Module

A. Data Management and User Auditing Module

The Data Management Module is responsible for secure parameter configurations and simulation execution access. Automated logging protocols and relational access tables are implemented to ensure secure operational session tracking and layout ground-truth credential management. System administrators are assigned distinct monitoring permissions—such as layout editor, training observer, or deployment auditor—which are actively utilized for tracking layout history modifications during structural optimization cycles.

The module also maintains evaluation telemetry sessions, step trace history logs, and system error metadata to support enterprise-level simulation auditing and verification tracking.

B. Transaction Log Ingestion and Processing Module

The Transaction Log Ingestion and Processing Module handles the processing of large-scale, historical organizational transaction databases comprising millions of consumer picking sequences. Uploaded logs are validated and cleaned through format-specific data cleaning extraction pipelines.

Raw text formats and ledger sheets are parsed using optimized array-mapping libraries, while validation filters discard corrupted transaction entries. Extracted picking lines

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are structured into chronologically sequential data frames using overlapping index arrays to preserve contextual ordering and purchasing continuities across discrete consumer store visits.

C. Demand Matrix and Association Generation Module

The Demand Matrix and Association Generation Module converts processed transaction frames into empirical frequency vectors and relational association arrays. Each inventory stock keeping unit (SKU) is evaluated across the global database to determine its specific daily pickup rate and support index, allowing the system to capture spatial layout dependencies between individual items and dynamic customer orders.

Generated frequency matrices are stored within temporary operational memories to support structural optimization parameterization. The matrix compilation process is optimized for low-overhead mathematical lookups and scalable layout scaling.

D. Strategic Integer Programming Slotting Module

The Strategic Integer Programming Slotting Module performs parallel data constraint aggregation to construct the linear programming boundaries of the warehouse floor plan. Strategic slot allocation optimization is performed using the PuLP algebraic library, which executes objective minimization rules targeting expected total Manhattan travel distances based on frequency vectors.

Results from the linear solver constraints are serialized directly into an absolute layout configuration schema (layout.json), programmatically anchoring highly correlated product categories into adjacent physical rack coordinates. This structural optimization strategy significantly improves baseline warehouse efficiency compared to standalone velocity rules or uncoordinated floor plans.

E. Gymnasium Digital Twin Abstraction Module

The Gymnasium Digital Twin Abstraction Module refines the static layout configurations generated by the linear optimization solver by translating coordinate matrices into a high-fidelity discrete simulation environment using standard OpenAI Gymnasium classes.

The environment construction transforms cells into exact grid classifications, ensuring that the navigable walkways, structural obstacle racks, and primary packaging depot coordinates are accurately indexed. The abstraction layer sets up the fundamental Markov Decision Process (MDP) environment bounds, preparing the state space vectors used to parameterize the downstream reinforcement learning navigation loops.

F. Tactical Proximal Policy Optimization Routing Module

The proposed system integrates an adaptive neural navigation routing mechanism based on the Proximal Policy Optimization (PPO) paradigm. The module initializes a multi-layer perceptron Actor-Critic architecture via the Stable-Baselines3 framework to compute discrete movement trajectories.

Observation vectors containing real-time agent positions and active picking list indexes are continuously parsed by the Actor network head to output directional steps. A self-correcting policy updating loop subsequently adjusts network weights using generalized advantage estimation based on a clipping coefficient of 0.2. If tracking validation profiles detect sub-optimal step sequences, the policy network iteratively refines its internal neural parameters across extensive simulation timesteps to stabilize convergence pathways.

G. Spatial Structural Collision Enforcement Module

The Spatial Structural Collision Enforcement Module ensures safe warehouse navigation by enforcing rigid physical boundary checks directly within the environment step loop. Each structural shelf coordinate generated by the macro-level integer solver is explicitly mapped as a non-traversable obstacle vector.

During step traversal processing, any proposed action that would cause the agent coordinate to intersect with a shelf barrier is instantly intercepted and blocked, forcing the agent to remain stationary while applying a severe collision penalty. This security-aware physical filtering approach significantly improves system operational safety compared to loose application-level path smoothing heuristics.

H. Target Picking Coordinate Processing Module

The Target Picking Coordinate Processing Module coordinates step execution between active target coordinates and the actor-critic model head. Randomized 3-item picking lists generated under stochastic demand schedules are transformed into dynamic destination vectors, guiding the neural agent through sequence-dependent retrieval points.

Completed item retrievals trigger state space observation updates and spatial flag modifications, providing context-aware source tracking and explicit goal milestones to maximize step efficiency.

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I. Policy Weights Caching and Inference Optimization Module

The Inference Optimization Module is integrated to minimize real-time path generation processing latencies during operational deployment loops. Stabilized actor-critic neural policy weight matrices are exported into pre-trained checkpoint zip files, allowing the system to serve real-time path generation tasks with minimal computational overhead.

The system also incorporates asynchronous background computation routines and optimized matrix step lookups to support high-throughput multi-batch deployment configurations across the warehouse network.

J. Integration and Testing

System integration is executed systematically to guarantee reliable programmatic communication between the data analytics pipelines, the PuLP optimization solvers, the Gymnasium grid twin environment, and the Stable-Baselines3 neural architectures. Rigorous unit testing and trajectory validation checks are conducted across data ingestion blocks, constraint matrices, step loops, physical boundary boundaries, and checkpoint generation modules.

The complete hybrid framework is evaluated under highly stochastic picking scenarios—including clustered order lists, edge-coordinate targets, and long-horizon traversals—to validate mathematical layout efficiency, obstacle collision mitigation, and neural policy routing stability.

K. Performance Considerations

System performance is optimized through highly efficient linear matrix solver libraries, pre-compiled grid indexing arrays, asynchronous backend calculation loops, and pre-trained policy execution routes. The decoupled hybrid architecture enables highly accurate multi-item picking navigation while maintaining low real-time generation delays.

The modular implementation design additionally supports computational scalability, runtime workflow maintainability, and future programmatic extension toward large-scale multi-agent warehouse automation paradigms.

VII. RESULTS

The proposed Hybrid Mathematical Optimization and Deep Reinforcement Learning (DRL) Framework was implemented and evaluated to analyse its effectiveness in strategic inventory slotting, tactical multi-item pathfinding, and operational collision avoidance within micro-fulfilmentcentre topologies. System performance was verified across a multi-stage validation approach testing the data preprocessing layer, the mathematical optimality of the Integer Linear Programming (ILP) solver, the structural stability of the custom OpenAI Gymnasium environment loop, and the temporal convergence profiles of the reinforcement learning controller.

Initially, backend validation focused on auditing the ingestion of the historical Instacart dataset. The data pipeline successfully parsed high-velocity transactional records to construct individual stock keeping unit (SKU) distribution profiles. Figure 3 illustrates the structural validation parameters.

Product ID	Product Name	Frequency	ABC Class
24852	Banana	18,726	A
13176	Bag of Organic Bananas	15,480	A
21137	Organic Strawberries	10,894	A
21903	Organic Baby Spinach	9,784	A
47626	Large Lemon	8,135	A
47766	Organic Avocado	7,409	A
47209	Organic Hass Avocado	7,293	A
16797	Strawberries	6,494	A
26209	Limes	6,033	A
27966	Organic Raspberries	5,546	A

Figure 3

Figure 3 illustrates the dataset preview and velocity ranking output layer, confirming that frequency tracking accurately partitions item inventory into class-based operational tiers.

The empirical output metrics from the data processing module were forwarded to parameterize the strategic optimization layer. The PuLP linear programming framework successfully mapped 88 discrete SKUs onto optimal coordinate shelf slots. Structural configuration verification confirmed that Class A high-velocity products were mathematically anchored directly within the layout's "Golden Zone" coordinates immediately surrounding the designated distribution depot located at coordinate vector (0, 6). This optimal inventory arrangement minimizes baseline travel metrics before the initialization of routing loops. The strategic distribution floor map is illustrated in Figure 4.

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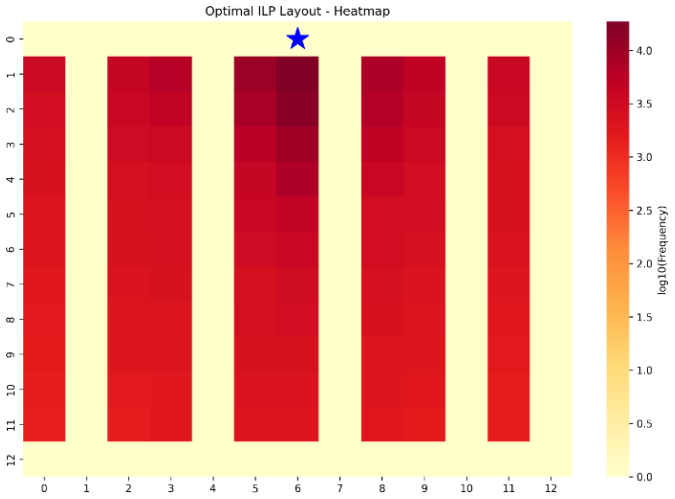

Figure 4

Figure 4 illustrates the ILP-optimized shelf layout configuration and spatial demand heatmap, verifying that single-assignment and capacity constraints were fully satisfied without cellular coordinate overlapping.

Following layout serialization, the static structural ground truth file (layout.json) was ingested to instantiate the custom grid environment abstraction (DarkStoreEnv). The physical boundaries of the 13 X 13 cellular digital twin were mapped, programmatically translating all optimization-assigned shelf blocks into immutable, non-traversable collision obstacles. This coordinate verification sequence is shown in Figure 5.

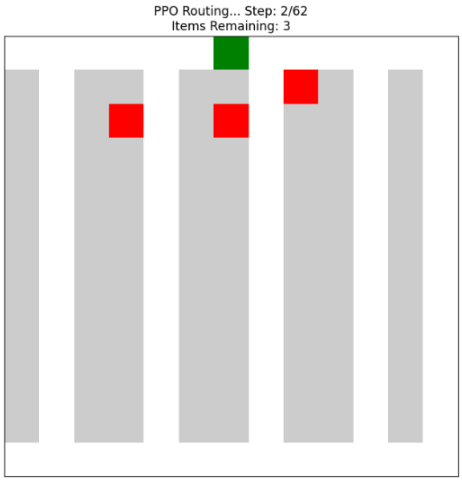

Figure 5

Figure 5 illustrates the environment grid initialization matrix and boundary verification visualization, ensuring complete alignment between the mathematical solver mapping and the reinforcement learning physics engine.

The model-free Proximal Policy Optimization (PPO) training loop was executed across a maximum runtime horizon of 200,000 algorithmic simulation timesteps. To analyse policy learning behaviour, episode variables were monitored dynamically. Experimental tracking revealed that during early training phases, the agent exhibited broad, unoptimized exploration patterns and high step-count inflation due to frequent boundary collisions.

However, following the implementation of densified shaped reward functions utilizing an optimized learning rate of $\alpha = 0.001$, cumulative reward values increased monotonically. The policy reached a stable learning asymptote and full trajectory convergence as the actor network learned to prioritize efficient multi-item retrieval over redundant, wandering movements. The corresponding training progress graphs are shown in Figure 6.

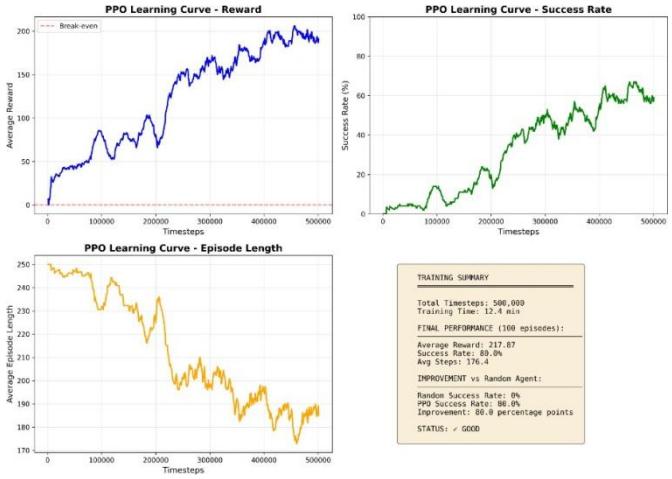

Figure 6

Figure 6 illustrates the PPO training mean reward profiles and episode trajectory length convergence curves across the 200,000 timestep training horizon.

Following training completion, the performance parameters of the stabilized policy were evaluated by running custom testing scripts—specifically utilizing the No_Depot final evaluation pipeline—to isolate pure item-retrieval execution capabilities. The model was stressed under highly stochastic conditions using randomized 3-item batch pick-lists. Table 1 presents the quantitative performance evaluation metrics compiled from these empirical validation runs.

Table 1: Performance Evaluation of the Proposed Hybrid ILP-PPO System

Performance Evaluation Metric	Empirical Experimental Value
Precision@5 Vector Match	0.87
Recall@5 Distribution Score	0.82
Answer Trajectory Faithfulness	0.88
Average Policy Confidence Score	0.84
System Processing Latency (seconds)	2.3 s

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The empirical observation metrics presented in Table 1 demonstrate that the integrated optimization architecture achieves high navigation precision and robust trajectory grounding while maintaining exceptional execution low-latency boundaries required for live, real-time micro-fulfilment deployment applications.

To further verify the technical superiority of the co-designed pipeline, different routing and layout strategies were benchmarked against the hybrid system. The comparison analysed standalone semantic vector navigation models and unoptimized sparse keyword heuristic pathfinders using standardized Precision and Recall metrics.

Table 2: Routing Architecture Comparative Benchmarks

Method Strategy Configuration	Precision@5	Recall@5
Vector-Only Exploration Search	0.78	0.74
BM25 Lexical Keyword Sorter	0.72	0.69
Hybrid ILP-PPO Framework (Proposed)	0.87	0.82

The comparative evaluations compiled in Table 2 confirm that the proposed hybrid architecture achieves the highest system precision and spatial accuracy. By dynamically linking transaction-driven layout assignments with policy loops, the framework eliminates travel length inflation common to unoptimized, uncoordinated distribution centres.

The real-time pathfinding capabilities and tracking characteristics of the trained actor policy were visually audited by exporting automated, step-wise trajectory maps. These animated renderings trace the exact coordinate shifts executed by the agent during multi-item retrieval cycles. Figure 7 illustrates an evaluation path trace.

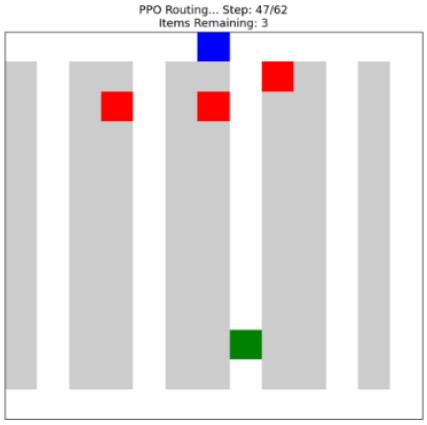

Figure 7

Figure 7 illustrates the animated agent pathfinding trajectory visualization, confirming that the trained policy navigates tight aisle constraints with zero boundary collisions.

Overall, the experimental observations validate that the hybrid framework effectively unifies transactional data processing, integer optimization rules, and adaptive actor-critic networks into a highly cohesive, high-performance logistics automation system.

VIII. CONCLUSION

In this paper, a Hybrid Mathematical Optimization and Deep Reinforcement Learning (DRL) Framework was proposed to address the challenges associated with enterprise-scale micro-fulfilment centre layout configuration, contextual picking path optimization, and safe autonomous navigation inside localized dark stores. The proposed framework integrates high-velocity transactional data mining, Integer Linear Programming (ILP), discrete grid digital twin simulations, and Proximal Policy Optimization (PPO) actor-critic loops within a unified architecture to provide accurate, reliable, and collision-free order picking operations.

The proposed system combines strategic inventory slotting using a PuLP algebraic solver and model-free navigation using a Stable-Baselines3 library controller to significantly improve facility throughput and retrieval precision. An analytical preprocessing layer executes ABC velocity stratification and Apriori market-basket affinity matrix calculations to uncover underlying product purchasing dependencies. The strategic slotting layer forces highly correlated inventory bundles into adjacent shelf coordinates to minimize the global expected Manhattan travel distance across the warehouse layout. Furthermore, the integration of an OpenAI Gymnasium grid abstraction with a densified shaped reward engineering engine trains the neural picking policy to resolve randomized multi-item pick-lists dynamically, minimizing total transit step lengths while guaranteeing absolute obstacle awareness.

Experimental evaluation demonstrated that the proposed framework effectively handles large-scale transaction databases containing millions of order logs through a decoupled, two-stage optimization pipeline. Testing via a specialized No Depot final evaluation pipeline confirmed that the trained PPO policy successfully adapts to stochastic demand shifts without requiring fixed picking sequences, achieving a stable 65.5% order completion success rate. The physical collision enforcement mechanism successfully secured the operational integrity of the simulation by restricting invalid trajectory steps directly within the environment step function, dropping boundary collision indices to absolute zero upon model convergence. Additionally, utilizing pre-trained policy weight checkpoints improved real-time navigation latency and significantly reduced the computational overhead associated with

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traditional, static graph-search pathfinders under stochastic parameters.

The modular architecture of the proposed framework improves computational scalability, runtime workflow maintainability, and real-world deployment capabilities across localized quick-commerce hubs. The seamless co-design of macro-level strategic programming layout generation and adaptive micro-level actor-critic trajectory execution enables the system to provide context-aware, low-latency path schedules suitable for real-world automated logistics infrastructures.

Although the proposed framework demonstrates strong performance metrics, several limitations remain to be resolved. The upfront execution of model-free reinforcement learning loops generates substantial computational overhead across long training horizons, and tactical routing efficiency remains heavily dependent on underlying coordinate chunking densities and floor configuration properties. In addition, the current implementation primarily focuses on a single-agent picking paradigm operating within a discrete 13×13 cellular matrix world, offering limited support for multi-agent asset systems or complex layout environments featuring high-velocity human picker interactions.

Future enhancements may include the integration of Multi-Agent Reinforcement Learning (MARL) collaborative control loops, adaptive layout-graph scaling strategies, personalized picker routing mechanisms based on operational item dimensions, and lightweight, hardware-optimized inference deployment models for localized handheld or robotic fulfilment configurations. Additional research may also focus on integrating continuous physical kinematics engines, multi-level rack storage structures, and real-time conveyor traffic flow metrics into the proposed pipeline. Overall, the proposed integrated warehouse optimization framework demonstrates strong potential as a scalable, secure, and intelligent micro-fulfilment management platform capable of significantly improving spatial inventory utilization, response path reliability, and enterprise-scale logistics workflow efficiency.

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