# AI-Augmented SLAM for Warehouse Robots

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## Abstract—

The rapid expansion of Industry 4.0 technologies has fundamentally changed the way warehouses operate. Today, logistics environments demand systems that are not just automated, but genuinely intelligent — capable of responding to real-time changes without human intervention. Autonomous Mobile Robots (AMRs) have emerged as a leading solution for tasks such as goods transport, inventory tracking, and logistics execution. However, most conventional AMR systems depend on static, pre-planned navigation routes that are unable to respond to moving people or dynamic obstacles, directly compromising both safety and operational efficiency.

This paper presents an AI-augmented autonomous mobile robot system that integrates vision-based Simultaneous Localization and Mapping (SLAM) for intelligent navigation within warehouse environments. The system uses LiDAR and camera-based perception to build real-time occupancy grid maps while continuously estimating the robot's position. Navigation is handled by the A* path planning algorithm, which identifies the most efficient route between any two points on the map. A dedicated AI-based risk assessment module monitors the environment continuously, evaluating factors such as human proximity, crowd density, and robot velocity to classify risk in real time and adjust the robot's behavior accordingly.

The architecture is built on a modular, distributed ROS2 framework, enabling scalability and efficient communication between system components. By combining sensor fusion, AI-driven decision making, and adaptive behavior control, the robot adjusts its speed and path dynamically while maintaining safe operation at all times.

The system was evaluated in a simulated warehouse environment containing both static and dynamic obstacles. Results demonstrated zero collisions, an efficiency rating of 85%, and successful navigation over 20 meters within 45 seconds. These outcomes confirm that the proposed approach meaningfully improves upon traditional static navigation systems, offering a reliable and scalable solution for intelligent warehouse automation.

**Keywords—** Autonomous Mobile Robot; SLAM; Artificial Intelligence; Warehouse Automation; ROS2; Path Planning; Industry 4.0

## I. INTRODUCTION

Modern warehouses are no longer simple storage facilities. They are high-throughput logistics systems where speed, accuracy, and safety must coexist. As supply chains grow more complex, the pressure to automate has intensified across the industry. Autonomous Mobile Robots have become a central part of this transformation, taking over repetitive and physically demanding tasks such as material transport, order picking, and inventory management.

Unlike traditional Automated Guided Vehicles (AGVs), which depend on fixed tracks or embedded infrastructure, AMRs are designed to navigate freely and adapt to changing environments. This flexibility makes them well-suited to warehouses, where layouts shift and human workers operate alongside machines. However, this same flexibility introduces a set of technical challenges that must be carefully addressed.

The most significant challenge is navigating environments that are only partially known or that change in real time. Simultaneous Localization and Mapping (SLAM) provides the foundational capability here, allowing a robot to construct a map of its surroundings while simultaneously tracking its own position within that map. But SLAM alone is not sufficient. A robot also needs to reason about what it perceives — to assess whether a detected human or object poses a risk, and to decide how to respond.

Dynamic obstacles such as human workers, forklifts, and other robots are particularly problematic for conventional planning algorithms like A* and Dijkstra's when used without real-time adaptation. These algorithms are highly effective for static environments, but require intelligent augmentation to handle a world that keeps changing.

This project addresses that gap by combining SLAM, A* path planning, and an AI-based risk assessment and behavior control system into a unified, modular architecture. The result is a robot that can navigate efficiently, detect and respond to human presence intelligently, and reroute itself dynamically when its planned path is blocked.

The main objectives of this work are:

- To develop an autonomous mobile robot system augmented with AI-based decision making.
- To integrate SLAM for real-time environment mapping and self-localization.
- To implement an intelligent risk assessment framework that enables safe, adaptive behavior in the presence of dynamic obstacles.

## II. LITERATURE REVIEW

There have been significant advancements in technologies related to autonomy recently. Significant achievements have been made in fields of robot navigation, perception, and decision making. Below is described the review of current researches on SLAM, path planning, and AI integration in robotics.

A. SLAM Algorithms

There exists a number of ways of solving the SLAM problem. LiDAR-based algorithms (Gmapping and Hector SLAM) provide very precise results. Such algorithms are widely used in practice because they can operate only under the condition of using laser scanning for building the map. Algorithms based on vision (e.g., ORB-SLAM) use the information provided by a camera and rely on images to identify how far the robot went. Despite being cheap, vision-based solutions can be affected by changes in lighting conditions. The combination of those techniques is suggested as the means of enhancing performance.

B. Path Planning Algorithms

Algorithms of this type are important for navigation purposes. Classic methods like A* and Dijkstra's algorithms guarantee both optimality and completeness. However, they can be applied only to static environments. The dynamic versions of those include Dynamic A* and D* Lite which are able to recompute the optimal solution instantly due to changes in environment.

C. AI Integration in Robots

Nowadays, there exists a trend to use AI technology to improve the navigation system. For example, machine learning can be helpful in identifying objects, tracking people, and forecasting future actions. Convolutional neural networks are widely used for that purpose because they improve the precision of recognition. At the same time, many algorithms solve particular problems without integrating them into navigation solutions.

D. Research Gap

Significant improvements in those fields were reached recently. However, the development of the unified solution combining all the three aspects still needs to be improved. There is a critical necessity of implementing SLAM algorithms along with risk assessment and behavior-based control. That is what our project attempts to do.

## II. METHODOLOGY

The proposed system is organized around a structured processing pipeline that moves from perception through to action. Each stage is handled by a dedicated module, and all modules communicate through a ROS2-based distributed architecture that ensures scalability, fault isolation, and real-time responsiveness.

Perception and Sensor Fusion. The robot perceives its environment through a combination of LiDAR and camera inputs. These two data streams are fused to produce a richer, more reliable picture of the environment than either sensor alone can provide. LiDAR contributes precise distance measurements across a wide angular range, while the camera adds contextual information useful for identifying objects and human presence. The fused output feeds directly into the SLAM module.

SLAM and Occupancy Grid Mapping. SLAM processes the fused sensor data to simultaneously build a map of the warehouse environment and estimate the robot's position within it. The output is an occupancy grid — a 2D representation of the environment where each cell is classified as free, occupied, or unknown. This grid is updated continuously as new sensor data arrives. In the simulation, the occupancy grid is a 20×20 matrix initialized with known rack positions and dynamically updated as human workers move through the space. The robot's current position is tracked at each step, satisfying the localization requirement of SLAM.

Path Planning with A*. Route planning is handled by the A* algorithm, which operates on the occupancy grid. A* evaluates candidate paths using the function $f = g + h$, where $g$ is the actual cost from the start to the current cell and $h$ is a heuristic estimate of the remaining cost to the goal. The system uses Chebyshev distance as the heuristic, which accounts for 8-directional movement including diagonals. A* finds the shortest valid path through free cells, routing around all static obstacles. When dynamic rerouting is triggered, A* replans using a temporary version of the grid in which human positions are also marked as obstacles, ensuring the new path avoids them.

AI-Based Risk Assessment. A risk assessment module runs every control cycle. It evaluates three weighted factors: proximity (how close the nearest human is, weighted 1.2), density (how many humans are in the vicinity, weighted 0.8), and velocity (the robot's current speed, weighted 0.6). The weighted sum is passed through a sigmoid function to produce a continuous risk score between 0 and 1. This score is then compared against defined thresholds to determine the robot's behavioral state: NORMAL (score below 0.65), CAUTION (above 0.65), SLOW (above 0.85), or STOP (above 0.90).

Dynamic Rerouting. Each cycle, the system inspects the three steps immediately ahead on the planned path. If any of those positions are occupied by a human, a rerouting event is triggered. The A* planner recomputes the route using the updated grid, producing a new path that avoids the blockage. This lookahead rerouting mechanism ensures the robot responds proactively rather than waiting until a collision is imminent.

Behavior Control. The robot's movement is directly controlled by its behavioral state. In NORMAL and CAUTION states, it advances along the planned path at its current velocity. In SLOW state, it continues but at a reduced speed. In STOP state, it holds its position until the risk score drops to a safer level and rerouting

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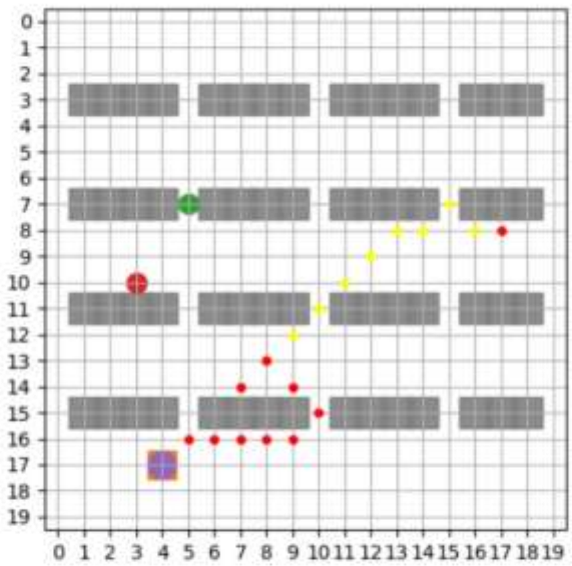
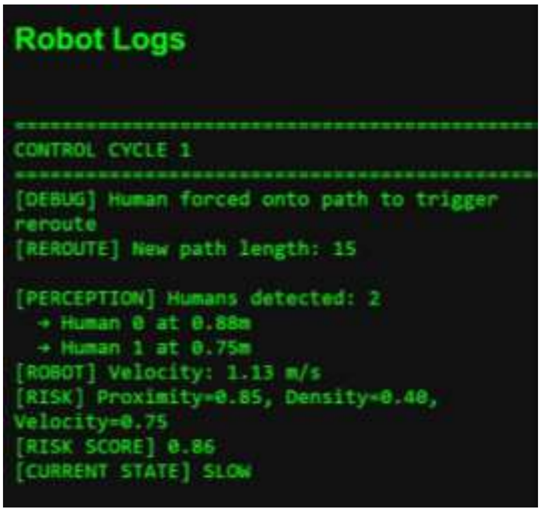
produces a clear path. This layered response ensures smooth operation under typical conditions while guaranteeing hard stops when necessary.


Methodology Adopted



Warehouse Robot Simulation and Rerouting




Robot Logs

## III. RESULTS AND DISCUSSION

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Table I: Performance Metrics

| Metric | Value |
|---|---|
| Path Length | 20 m |
| Navigation Time | 45s |
| Efficiency | 85% |
| Collsion Rate | 0% |

Compared to conventional navigation frameworks that rely on static pre-planned paths, the proposed system showed clear advantages in responsiveness, safety, and adaptability. The integration of AI-driven decision making with real-time SLAM enabled a more nuanced and situationally aware approach to navigation, one that goes beyond simply finding a path and instead manages how and when the robot moves based on a continuous understanding of its environment. These results indicate that the system is well-suited for deployment in real logistics environments and that the approach scales naturally to more complex settings.

Warehouse Robot Hardware Prototype

## IV. CONCLUSION

This paper has presented an autonomous mobile robot system that brings together SLAM-based environment mapping, A* path planning, and an AI-driven risk assessment and behavior control module into a single integrated architecture. The system is designed to operate safely and efficiently in warehouse environments where both static and dynamic obstacles must be managed in real time.

The evaluation results demonstrate that the approach achieves its core objectives: zero collisions, efficient navigation, and reliable real-time rerouting in the presence of human workers. The modular ROS2-based design also ensures that individual components can be upgraded or extended without disrupting the overall system.

Future work will focus on incorporating deep learning-based perception for improved human detection and intent prediction, extending the system to coordinate multiple robots operating within the same space, and conducting physical deployment trials to validate performance under real-world conditions beyond the current simulation.

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