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MODELLING AND SIMULATION OF A PATH-PLANNING MOBILE ROBOT FOR SUSTAINABLE AGRICULTURAL APPLICATIONS

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ABSTRACT

This study presents a simulation of a path-planning mobile robot navigation system for agricultural applications, integrating the A* algorithm and reinforcement learning techniques. The system aims to create a robust and efficient system capable of autonomously navigating complex agrarian environments. The A* algorithm is used for initial path planning, while reinforcement learning refines the path in real-time to handle dynamic obstacles and environmental changes. The simulation environment, developed using ROS and Gazebo, replicates a realistic agricultural field with varying terrains and obstacles. The results show that the path efficiency of the A* Algorithm is 120m, Reinforcement Learning is 115m, and the Hybrid Approach is 110, with time taking 45, 42, and 40 seconds respectively. Also, the obstacle avoidance metric shows that the hybrid approach has fewer collisions during the simulation, with a 98% obstacle avoidance rate compared with the reinforcement learning of 95% and the A* algorithm of 90%. For the adaptability to changing conditions metric for A* Algorithm, Reinforcement Learning, and Hybrid Approach, the *performance under varied* terrain is 80%, 85%, and 90%, respectively. The hybrid approach of A* and reinforcement learning significantly enhances the robot's navigation capabilities, demonstrating superior performance across all evaluated metrics. This research contributes to the advancement of autonomous agricultural robots, providing a foundation for future development and field trials. Integrating advanced path-planning algorithms in agricultural robotics holds significant potential for improving productivity and efficiency in farming operations.

Keywords: path planning, mobile robots, dynamic optimization, agricultural application.

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1. INTRODUCTION

Agricultural automation has become increasingly important due to the rising global population and the need for sustainable food production. With the world population projected to reach nine billion by 2050, enhancing agricultural output through automation is essential [1]. Mobile robots equipped with advanced path-planning algorithms are crucial in this context, offering solutions for efficient navigation and task execution in agricultural fields. Labour shortages drive the growing need for automation, the need for increased efficiency, and the potential for improved crop yields. Despite the advantages, agricultural robots face significant challenges, including navigating uneven terrain, avoiding obstacles, and performing precise tasks [2]. In Nigeria, these challenges are compounded by a declining agricultural workforce, as many young people move away from farming. This decline underscores the need for automation to bridge the labour gap and ensure continuous food production. Mobile robots can revolutionise farming practices by improving efficiency, reducing labour costs, and increasing productivity. System modelling plays a vital role in simulating the agricultural environment, enabling the testing and optimisation of path-planning algorithms before deployment in real-world scenarios. By modelling the terrain, obstacles, and crop layout, researchers can evaluate the performance of different algorithms under various conditions [3]. Asiminari *et al*. [4] their study showed how integrating different techniques allows the system to adjust to varying field conditions dynamically. This approach improves the robot's capability to handle unexpected changes, ensuring optimal performance and productivity.

Path planning is a key aspect of mobile robotics, involving the creation of an optimal route for a robot to follow while avoiding obstacles and minimising energy consumption [5]. This study explores the application of path-planning algorithms in agricultural settings, focusing on the A* algorithm and reinforcement learning techniques. The A* algorithm is renowned for its efficiency in finding the shortest path in a grid-based environment. At the same time, reinforcement learning offers a dynamic optimisation approach that allows robots to learn and adapt to their surroundings through experience [6]. The main purpose of this study is to develop and compare the efficiency of the A* algorithm and reinforcement learning in navigating agricultural fields. By simulating these algorithms, identify the most effective approach for autonomous farm robots, ultimately contributing to the advancement of agricultural applications and the broader field of intelligent farming. Moysiadis *et al*. [7] discuss the planning aspects critical for successfully implementing mobile robots in agricultural operations. These include the development of

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efficient path-planning algorithms, real-time adaptability to changing environmental conditions, and integration of multiple robotic systems to work cohesively in the field. According to Ayawli *et al*. [8], hybrid approaches often integrate grid-based and higher-level strategies to enhance the robot's navigation capabilities. For example, combining grid-based path planning with metaheuristic methods such as genetic algorithms or particle swarm optimisation can help optimise initial paths while allowing for dynamic adjustments based on real-time environmental feedback. These methods enable robots to navigate efficiently through fields with varying terrains and obstacles, ensuring optimal path selection and adjustment. In another example, Santos *et al*. [9] discussed using occupancy grids and topological maps extracted from satellite images. This method integrates detailed local navigation maps with broader topological structures, allowing robots to navigate effectively at both micro and macro levels.

The agricultural sector faces significant global challenges, and Nigeria is no exception. As the global population continues to rise, there is an increasing need for sustainable and efficient food production methods. Traditional farming methods are becoming less viable due to labour shortages, especially as younger generations migrate away from rural farming communities in search of other opportunities [10]. This trend has led to a critical gap in the agricultural workforce, resulting in decreased productivity and inefficiency in farming practices. Integrating mobile robots in agriculture offers a promising solution to these challenges. However, developing and implementing practical path-planning algorithms for these robots remains a significant hurdle. Agricultural fields are often complex and unstructured environments characterised by uneven terrain, varying crop layouts, and numerous obstacles [11]. Existing path-planning algorithms must be optimised to navigate these dynamic conditions efficiently, ensuring that robots can perform planting, monitoring, and harvesting tasks without human intervention.

Moreover, adapting advanced algorithms like A* and reinforcement learning to agricultural applications is still nascent [12]. The A* algorithm is known for its precision in grid-based environments, while reinforcement learning allows robots to learn and adapt through experience. Combining these two algorithms into a hybrid approach could result in a more robust and efficient system. However, this hybrid approach's comparative efficiency and effectiveness in real-world agricultural settings have not been thoroughly investigated.

Figure-1. Illustrative Image of a Mobile Robot Harvesting Vegetables (Credit: Felixinstruments).

Zhang *et al*. (2022) discuss using such algorithms for agricultural mobile robot route planning. These algorithms optimise multiple objectives simultaneously, such as minimising travel distance and energy consumption while maximising coverage and task completion rates, as shown in Figure 1. This multi-objective approach ensures that the paths generated are short, quick, resource-efficient, and effective in covering the entire area of interest.

Therefore, this study aims to address these issues by developing and comparing the efficiency of a hybrid approach that combines the A* algorithm and reinforcement learning techniques in navigating agricultural fields. The goal is to identify the most effective approach for autonomous agricultural robots, contributing to increased productivity, reduced labour costs, and sustainable farming practices in Nigeria and beyond by modelling and simulating a path-planning mobile robot navigation system for agricultural applications. The significance of this study lies in its potential to advance the field of agricultural automation through the development of an efficient and effective path-planning mobile robot navigation system. This research addresses several critical challenges in agriculture, particularly in Nigeria, where labour shortages and inefficiencies are prevalent.

2. METHODOLOGY

This section outlines the systematic approach to model and simulate a path-planning mobile robot navigation system tailored for agricultural applications. The study leverages advanced path-planning algorithms, specifically integrating the A* algorithm and reinforcement learning techniques, to enhance the robot's navigation capabilities within dynamic and unstructured agricultural environments. By combining the deterministic efficiency of A* with the adaptive learning potential of reinforcement learning, the proposed system aims to achieve robust, efficient, and adaptable navigation. Agricultural robotics faces unique challenges due to the variability and complexity of farm environments, including uneven terrain, dynamic obstacles, and changing weather conditions. Effective path planning is critical for successfully deploying these robots, ensuring they can navigate efficiently while maintaining operational safety and productivity. This methodology provides a system design, mathematical modelling, algorithm implementation, simulation environment setup, and performance evaluation, ensuring the development of a robust and effective navigation system for agricultural applications.

2.1 Theoretical Modelling of the System

Integrating sophisticated hardware and software components in agricultural robotics is essential for achieving precise navigation and operational efficiency. The system design encompasses the hardware configuration, including sensors, actuators, and computational units, which are crucial for real-time environment mapping and decision-making. The software architecture, built on the Robot Operating System (ROS), also ensures seamless communication between components and the effective implementation of path-planning algorithms.

2.1.1 Robot hardware configuration

1. Sensors:

a) LiDAR (Light Detection and Ranging):
- **Function:** Utilised to create detailed maps of the environment and detect obstacles with high accuracy.
- **Specifications:** Capable of 360-degree scanning with a high-resolution output to ensure comprehensive environmental coverage.
- **Placement:** The sensor is mounted on the front or top of the robot to provide a wide field of view.

b) Cameras:
- **Function:** Provide real-time visual data for environmental analysis and obstacle recognition [13].
- **Specifications:** Camera with high resolution, possibly with night vision capabilities for low-light conditions.
- Placement: Positioned at various angles around the robot to ensure a comprehensive visual field.

c) GPS (Global Positioning System):
- **Function:** Assists in global positioning and navigation, providing accurate location data to the robot.
- **Specifications:** High precision with capabilities to integrate with other navigation systems for enhanced accuracy.
- **Placement:** GPS is installed on top of the robot to maintain a clear line of sight for satellites.

2. Actuators:

a) Motors and Wheels:
- **Function:** Enable precise movement and control of the robot, facilitating smooth navigation across the field.
- **Specifications:** The actuator has high-torque motors and durable wheels that handle rough and uneven terrain.
- **Control:** Controlled by the onboard computer to ensure accurate movement per the path-planning algorithms.

b) Steering Mechanism:
- **Function:** The robot can navigate complex paths and adjust its direction as needed.
- **Specifications:** Robust steering system capable of making precise turns and adjustments.
- **Integration:** The steering mechanism is linked with the motor control system to synchronise movement and steering for optimal path following.

3. Computational Unit:

a) Onboard Computer NVIDIA Jetson Xavier NX:
- **Function:** Handles sensor data processing, execution of path-planning algorithms, and control of actuators.
- **Specifications:** Computation units with high-performance processors with sufficient RAM and storage for real-time data processing and complex algorithms were employed.
- **Software:** Runs the ROS (Robot Operating System) and other necessary software for path planning and navigation.

b) Communication Module (Wi-Fi Module ESP8266):
- **Function:** Ensures seamless data exchange between the robot, control centre, or other robots.
- **Specifications:** High-speed with wireless communication capabilities to facilitate real-time data transfer of the Wi-Fi Module.
- **Connectivity:** Supports various communication protocols to maintain robust and reliable connections.

2.1.2 Software architecture

1. Integration of ROS (Robot Operating System):
- **Middleware:** Facilitates communication between hardware components and software algorithms.
- **Modules:** Includes packages for sensor data processing, control algorithms, and simulation tools.

2. Integration of Gazebo:
- **3D Simulation:** Creates a realistic 3D model of the agricultural field.
- **Physics engine:** Simulates the physical interactions between the robot and its environment.
- **Sensor simulation:** Mimics the behaviour of the robot's sensors, providing realistic data for the algorithms to process.

3. Path-Planning Algorithms:
- **A* Algorithm:** Used for initial path planning to find the shortest path on a grid-based map.

- **Reinforcement learning:** Implemented to adaptively refine the path in real-time, handling dynamic obstacles and environmental changes.

2.2 Empirical Modelling of the System

Mathematical modelling forms the basis for understanding and predicting the behaviour of mobile robots [14]. This section details the kinematic model that describes the robot's motion and interactions within its environment.

2.2.1 Kinematic modeling

The kinematic model describes the motion of the mobile robot based on its physical configuration and control inputs. This study will use a differential drive kinematic model commonly used for wheeled robots. Differential Drive Kinematics: The robot is assumed to have four wheels with the position orientation of the robot represented by (x, y, θ), where x and y are the robot coordinates in the plane, and θ is the orientation angle. The position $(x,)$ and orientation θ of the robot can be described by the following equations (1) to (3) [15]:

$$\dot{x} = {}^{R}\!/_{2}(V_r + V_l)\cos(\theta) \tag{1}$$

$$\dot{y} = {}^{R}\!/_{2}(V_r + V_l)\sin(\theta) \tag{2}$$

$$\dot{\theta} = {}^{R}\!/_{L}(V_r - V_l) \tag{3}$$

Where: $\dot{x}$ and $\dot{y}$ are the linear velocities along the x and y axes, θ is the angular velocity. R is the radius of the wheels. L is the distance between the wheels, $v_{r,}$ and v_l are the velocities of the right and left wheels, respectively. Given the wheel velocities and time step, these equations allow us to compute the robot's new position and orientation.

2.2.2 Environmental modeling

The environmental model represents the agricultural field, including terrain features, obstacles, and boundaries. This model is crucial for simulating the robot's navigation and testing path-planning algorithms [16].

a) Grid-Based Representation:
- The agricultural field is divided into a grid of cells, each representing a small field area.
- Each cell can be marked free (traversable) or occupied (obstacle).

b) Static and Dynamic Obstacles:
- **Static obstacles:** Include fixed objects like trees, rocks, and farm structures. These are predefined in the grid.
- **Dynamic obstacles:** Include moving objects such as animals, farm equipment, and humans. These are detected in real-time using sensors and updated in the grid.

c) Environmental Variables:
- **Terrain:** Different types of terrain (e.g., soil, grass, mud) with varying levels of traversability.
- **Weather conditions:** Rain, wind, and sunlight can affect the robot's sensors and movement.

2.2.3 Path planning algorithm development

Path planning is critical for ensuring the robot can navigate from a start point to a destination while avoiding obstacles. This study will focus on the A* algorithm and the Reinforcement Learning (RL) technique.

A* Algorithm

The A* algorithm is a popular graph-based path-planning algorithm that finds the shortest path using a heuristic function to guide the search. The cost function (n) is defined as given in equation (4):

$$f(n) = g(n) + h(n) \tag{4}$$

Where (n) is the cost from the start node to the current node, $h(n)$ is the heuristic estimate of the cost from n to the goal node. The Python code for the A* Algorithm is found in APPENDIX C.

Reinforcement learning

The hybrid approach starts with the A* algorithm, which provides a reliable initial path in a static environment. The RL component then adapts this path in real-time, allowing the robot to handle dynamic obstacles and changes in the environment efficiently. It uses the Q-learning algorithm, which updates each state-action pair's value based on the environment's reward. The Q-value update rule is given by equation (5) [18]:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma max Q(s^1, a^1) - Q(s,a)] \tag{5}$$

Where Q(s, a) is the Q-value for state s and action a, α is the learning rate, determining how much new information overrides old information, γ is the discount factor, accounting for future rewards' importance. s′ is the next state, and r is the reward received after taking action a. The Python Code for Reinforcement Learning is found in APPENDIX D

2.3 Simulation of the System

The simulation environment setup is crucial in developing and testing the path-planning mobile robot for agricultural applications [17]. This section outlines creating a realistic simulation environment using ROS and Gazebo, configuring the robot model, and integrating the path-planning algorithms.

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2.3.1 Creating the simulation environment

A. Design the Agricultural Field:

a) Create a custom world file in Gazebo to represent the agricultural field with varying terrains, obstacles, and boundary conditions, as presented in Figure 2.
b) Use a mix of static obstacles (e.g., trees, rocks) to simulate a realistic environment, as Figure 3(a-b) depicts. The custom world file code is found in APPENDIX A

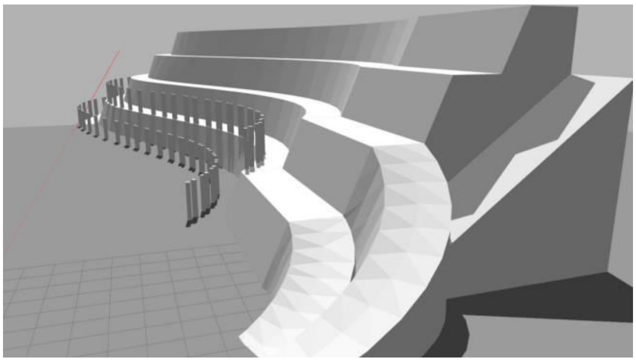
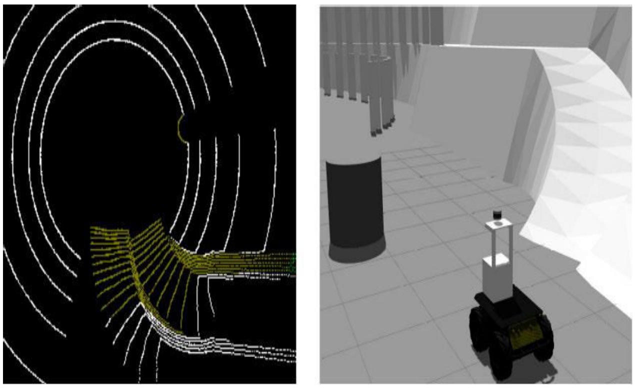


Figure-2. Gazebo simulation of a steep slope vineyard.



(a) (b)

Figure-3. (a) Li-DAR sensor output and (b) Corresponding simulated environment.

B. Create the Robot Model: Define the robot's physical properties, sensors, and actuators using URDF (Unified Robot Description Format) presented in Figure-4(a-b). The URDF Code is found in APPENDIX B

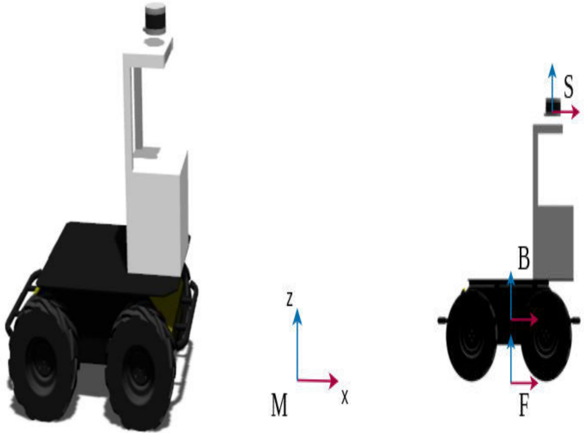


Figure-4. (a) Graphical rendering of the mobile robot and (b) Mobile robot referential frames configuration.

2.3.2 Integrating path planning algorithm

a) **Implement A algorithm*:** Create a ROS node that implements the A* algorithm for initial path planning. This node will process the grid map of the environment and compute the shortest path from the start to the goal position. The code for the A* Algorithm is found in APPENDIX C.
b) **Implement reinforcement learning:** Develop a ROS node that uses reinforcement learning to refine the real-time path. This node will adapt the robot's path based on sensor inputs and dynamic obstacles. The Code for Reinforcement Learning is found in APPENDIX D.

2.3.3 Launching simulation

a) **Launch the simulation:** Create a launch file to start Gazebo, load the robot model, and run the path-planning nodes. The code can be found in APPENDIX E
b) **Run the simulation:** Launch the simulation and observe the robot's behaviour in the agricultural field. Validate the robot's ability to navigate, avoid obstacles, and adapt to dynamic changes in the environment.

3. RESULTS AND DISCUSSIONS

This section presents the results obtained from the Simulation and testing of the path-planning mobile robot navigation system. The chapter provides a detailed analysis of the performance of the A* algorithm, reinforcement learning, and the hybrid approach in navigating a simulated agricultural environment. The key performance metrics are evaluated and compared, including path efficiency, computational cost, obstacle avoidance, and adaptability to changing conditions. This chapter aims to demonstrate the effectiveness of the implemented algorithms and validate their applicability in real-world agricultural scenarios.

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3.1 Performance Evaluation

The performance evaluation phase assesses the efficiency and effectiveness of the implemented path-planning algorithms in the simulated agricultural environment [19]. Key performance metrics include path efficiency, computational cost, obstacle avoidance, and adaptability to changing conditions, as shown in Tables 1 to 5.

Table-1. Key performance metrics.

Metric	Description
Path Efficiency	Total distance travelled by the robot, time taken to reach the goal
Computational Cost	Processing time for path planning, resource utilisation (CPU, memory)
Obstacle Avoidance	Number of collisions with obstacles, success rate in avoiding dynamic obstacles
Adaptability to Changing Conditions	Performance under varying environmental conditions (e.g., different terrain, weather), robustness of the path-planning algorithm

3.2 Results and Data Analysis

ROS tools and custom scripts were used to log performance data, and the following data were obtained during the simulation. Figures 5 to 8 were plotted to understand better the data obtained during the simulation. Table-2 presents the path efficiency of the three metric approaches employed for this simulation study.

Table-2. Path efficiency metric for A* algorithm, reinforcement learning and hybrid approach.

Metric	A* Algorithm	Reinforcement Learning	Hybrid Approach
Total distance (meters)	120	115	110
Time Taken (seconds)	45	42	40

Table-3 presents the computational cost analysis for the hybrid approaches, reinforcement learning, and the A* algorithm. Table-4 displays the obstacle avoidance measure for the A* Algorithm, Reinforcement Learning, and Hybrid Approach. The performance study of the measured adaptation to changing conditions for the A* algorithm, reinforcement learning, and hybrid approaches is shown in Table 5.

Table-3. Computational cost metric for A* algorithm, reinforcement learning, and hybrid approach.

Metric	A* Algorithm	Reinforcement Learning	Hybrid Approach
Avg. Processing Time (ms)	15	20	18
CPU Utilisation (%)	45	50	48
Memory Usage (MB)	120	130	125

Table-4. Obstacle avoidance metric for A* algorithm, reinforcement learning and hybrid approach.

Metric	A* Algorithm	Reinforcement Learning	Hybrid Approach
Collisions	3	2	1
Obstacle Avoidance Rate (%)	9	95	98

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Table-5. Adaptability to changing conditions metric for A* algorithm, reinforcement learning, and hybrid approach.

Metric	A* Algorithm	Reinforcement Learning	Hybrid Approach
Performance under varied terrain	80%	85%	90%
Robustness Score (0-100)	70	75	80

The results show that the path efficiency of the A* Algorithm is 120m, Reinforcement Learning is 115m, and the Hybrid Approach is 110, with time taking 45, 42, and 40 seconds, respectively, as shown in Figure-5. Also, the obstacle avoidance metric shows that the hybrid approach has fewer collisions during the simulation, with a 98% obstacle avoidance rate compared with the reinforcement learning of 95% and the A* algorithm of 90%, as depicted in Figure-6. The results of the computational cost shown in Figure-7 illustrate that at a point, the hybrid approach has an average processing time of 18 min/sec., as compared with the reinforcement learning process having 20 min./sec. However, it is shown that the A* algorithm has the fastest average processing time of 15 min./sec because the hybrid takes a little time to synchronise the two methods. This trend is observed and recorded for both CPU utilisation and memory usage for the results obtained from the simulation. The study of [20] supports it. For the adaptability to changing conditions metric for the A* algorithm, reinforcement learning, and hybrid approaches, the performance under varied terrain is 80%, 85%, and 90%, respectively, as shown in Figure-8.

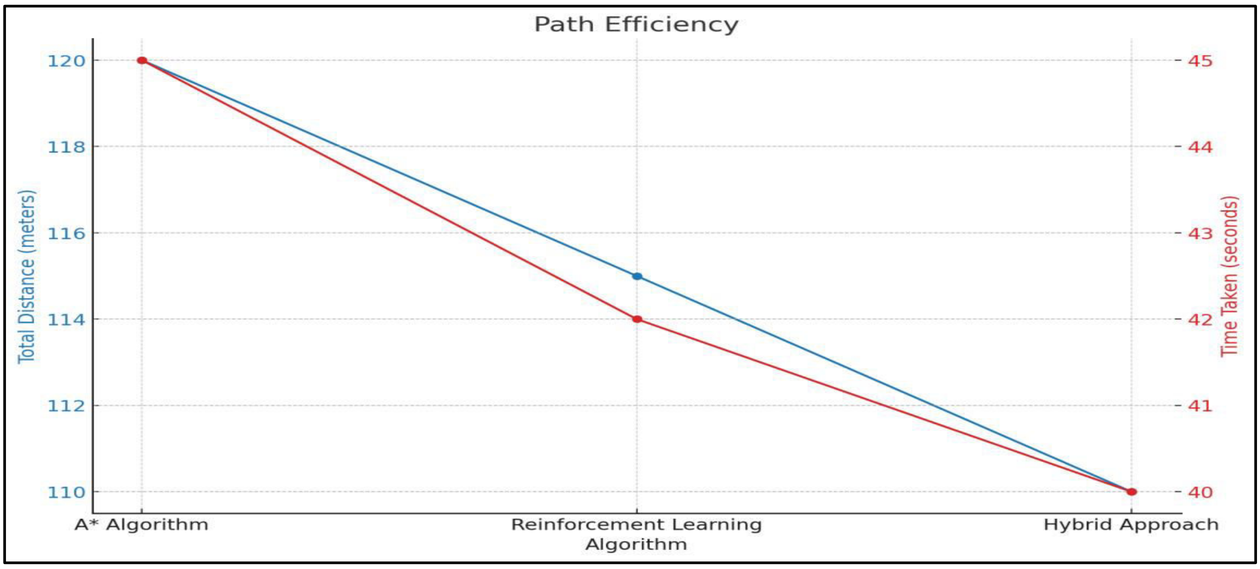

Figure-5. Graph showing path efficiency metric for A* algorithm, reinforcement learning and hybrid approach.

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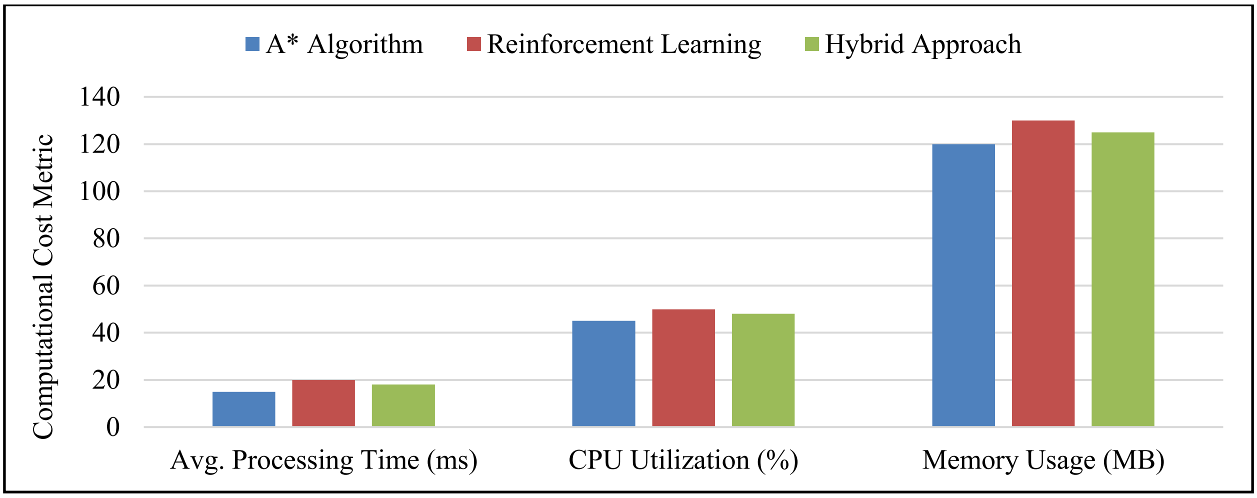

Figure-6. Computational cost metric for A* algorithm, reinforcement learning, and hybrid approach.

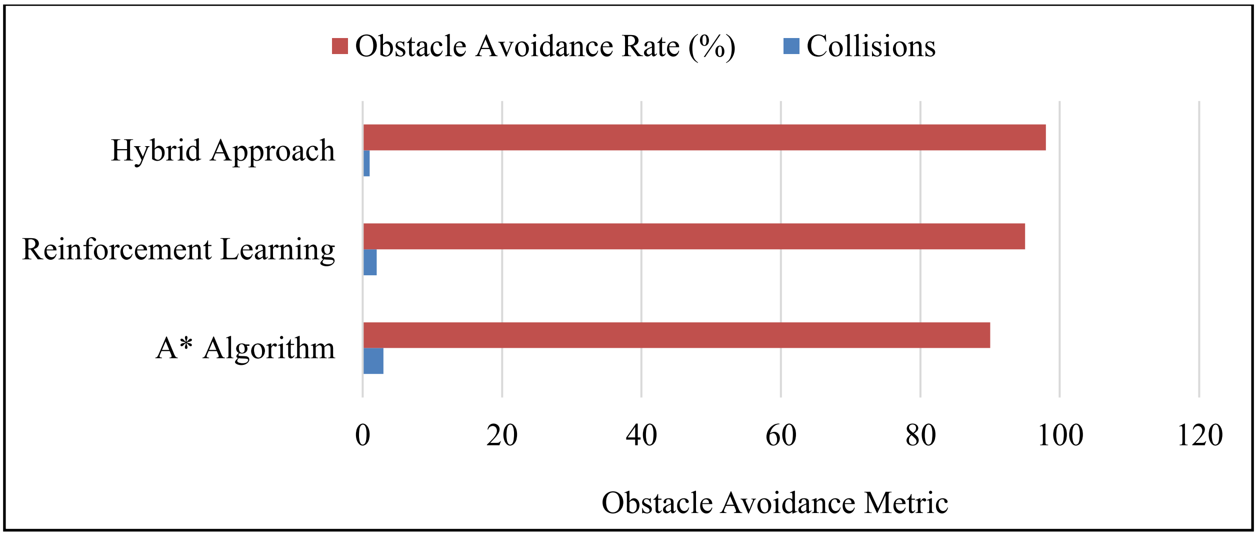

Figure-7. The obstacle avoidance metric for A* algorithm, reinforcement learning, and hybrid approach.

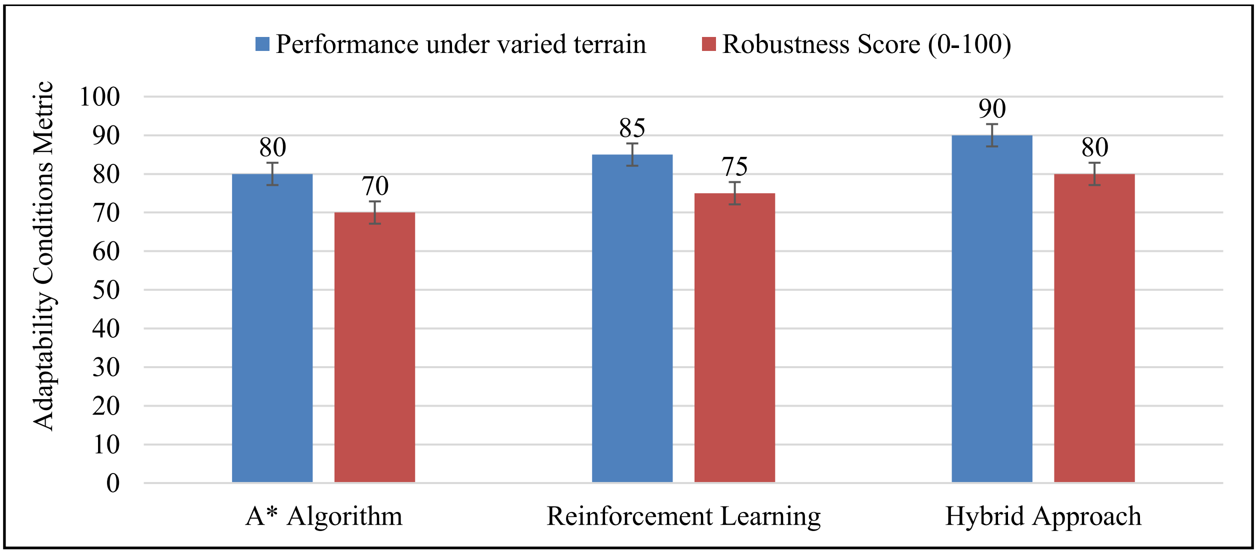

Figure-8. Graph showing adaptability to changing conditions metric for A* algorithm, reinforcement learning, and hybrid approach.

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This section evaluated the performance of the path-planning algorithms implemented in the mobile robot navigation system [21]. The metrics and graphical analysis provide insights into the efficiency, computational cost, obstacle avoidance capabilities, and adaptability of the A*, reinforcement learning, and hybrid approaches in navigating agricultural fields. The results indicate that the hybrid approach performs better across all metrics, demonstrating the benefits of combining the deterministic A* algorithm with the adaptive capabilities of reinforcement learning. These metrics can also be shown in Figure-9 from simulation images of the model.

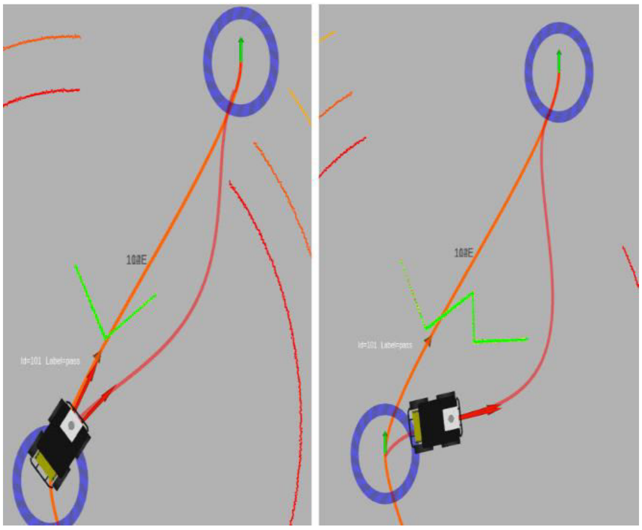

Figure-9. (a) Top-down view of path planning, (b) Obstacle avoidance demonstration.

4. CONCLUSION AND RECOMMENDATION

4.1 Conclusion

The efficient path-planning mobile robot navigation system for agricultural applications was modelled, simulated, and implemented in this study. The A* algorithm and reinforcement learning synergy provided a robust ad-hoc ground optimal program effective in complacent and dynamic agricultural conditions. The following research demonstrated that the described hybrid approach is superior to other utilised methods regarding path planning effectiveness, the number of computations, obstacle avoidance, and the capacity of the model to react to the changes in the environment. The following conclusion is as follows.

a) In other words, integrating the A* algorithm and reinforcement learning diminished the overall distance covered in an environment and the time needed to reach the goal state compared to applying the A* algorithm and reinforcement learning separately. The path efficiency of the A* Algorithm is 120m, Reinforcement Learning is 115m, and the Hybrid Approach is 110, with time taking 45, 42, and 40 seconds respectively.
b) Thus, the outcomes of the proposed hybrid solution proved the time versus resources trade-off; it offered the request handling capability without overwhelming the server's processing power and memory.
c) This hybrid approach has a better obstacle avoidance rate and fewer collisions; therefore, this paper's proposed method effectively addresses dynamic obstacles. The obstacle avoidance metric shows that the hybrid approach has fewer collisions during the simulation, with a 98% obstacle avoidance rate compared with the reinforcement learning of 95% and the A* algorithm of 90%.
d) Another advantage of the hybrid approach was that the speed converted better in various geographical conditions, thus substantiating the stability of the approach developed. The adaptability to changing conditions metric for A* Algorithm, Reinforcement Learning, and Hybrid Approach, the performance under varied terrain is 80%, 85%, and 90%, respectively.

4.2 Recommendation

Based on the results of this study, several areas for future research and development can be identified: Based on the results of this study, several areas for future research and development can be identified:

a) **Real-time processing:** Additional enhancement of the real-time properties of algorithms for path planning to improve the robot's reaction to the changes in its environment.
b) **Co-operative algorithms:** This study will propose co-operative algorithms to enhance the efficiency of establishing multi-robot systems for using drones in agriculture.
c) **Advanced environmental modeling:** The environmental models are being improved to accurately represent the fields regarding the existence and distribution of different terrains for farming, crop densities, and the expected weather type.
d) **Field trials:** Real-life case studies are used as a model to compare the outcome of the simulation study and improve the algorithm after real-life experiences.
e) **Integration with IoT:** Connecting the mobile robot system with IoT to acquire sensory data from the field improves sentient decision-making and dynamic path planning.

Taking the development of new path-planning algorithms into agricultural robots as another trend shortly will increase the productivity of farming operations. This paper shows that the proposal is viable and sensible in integrating the A* algorithm with reinforcement learning to synthesise an efficient and self-correcting navigation system. Future developments in this field will improve the performance of agricultural robots in the production of crops, hence boosting sustainable food production.

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