Development of an Algorithm for Autonomous Grass Cutting Robot

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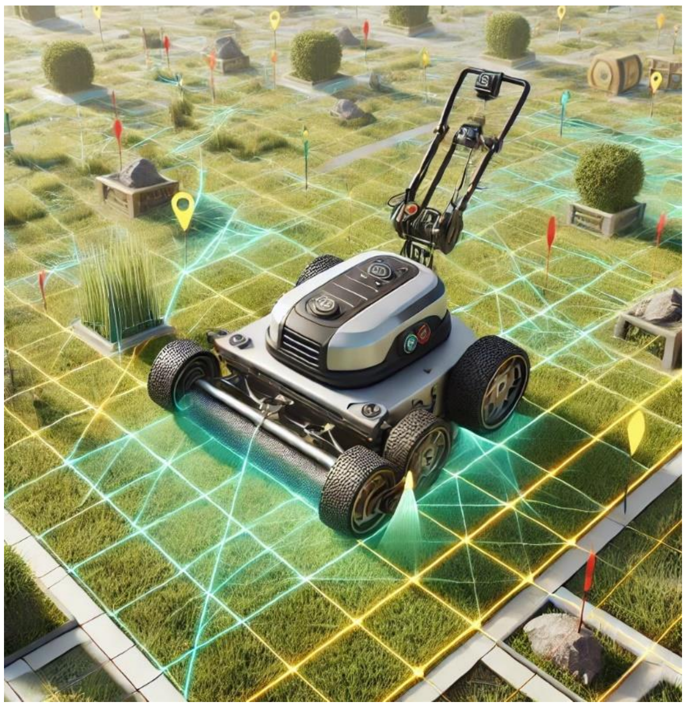
Abstract - Path planning is a critical area of research in robotics, with growing interest in developing methods to navigate obstacle-filled environments efficiently. In this paper, a custom pathfinding algorithm is proposed, designed to optimize navigation for an autonomous grass-cutting robot using backtracking and obstacle avoidance. The algorithm is tested alongside four well-established pathfinding algorithms—Genetic Algorithm (GA), Dijkstra's Algorithm, A* Pathfinding, and Breadth-First Search (BFS)—to evaluate performance in a 20x20 simulated grid environment mimicking a lawn with obstacles. The custom algorithm aims to ensure efficient obstacle avoidance and comprehensive coverage of the lawn, minimizing energy consumption. Performance metrics, such as path length, computational time, and overall efficiency, are used to compare the algorithms. While Dijkstra's consistently produces the shortest path and A* strikes a balance between computational demand and real-time application, the custom algorithm shows particular strength in handling complex obstacle patterns, reducing computational overhead. This study demonstrates the effectiveness of integrating backtracking and obstacle avoidance for autonomous lawn maintenance robots. The findings contribute to a deeper understanding of pathfinding algorithms and emphasize the potential of novel approaches for specific robotic applications.

Keywords: Path planning · Backtracking algorithm · Obstacle avoidance · Autonomous robot

I. INTRODUCTION

The challenge of generating an optimal path for autonomousrobots in complex, obstacle-filled environments has long been a prominent research area in robotics. While initial focus areas for path planning algorithms revolved around wheeled robots, the past few years have seen an increasing shift towards developing solutions for a wider variety of autonomous systems, such as robotic lawn mowers. These systems aim to autonomously navigate through irregular, cluttered environments to perform tasks like lawn maintenance without human intervention.

The rapid advancement of autonomous systems, particularly in consumer applications, has introduced new possibilities for AI-driven machines to perform traditionally manual tasks. Robotic lawn mowers, or robo-mowers, are an example of this transformation, offering enhanced efficiency, reduced labor costs, and consistent lawn care. However, for robo-mowers to operate effectively, they must be equipped with highly efficient navigation systems capable of avoiding obstacles such as trees and flower beds while optimizing energy consumption due to battery constraints. Pathfinding algorithms form the core of these navigation systems, enabling autonomous machines to navigate through their environment while avoiding obstacles. The algorithms determine the most efficient route by balancing the need for comprehensive coverage with the limitations imposed by computational capacity and energy resources. For robotic lawn mowers, selecting the right pathfinding algorithm is crucial to achieving optimal performance in terms of path length, time efficiency, and adaptability to environmental changes. This research focuses on evaluating four widely recognized pathfinding algorithms—Genetic Algorithm (GA), Dijkstra's Algorithm, A* Pathfinding, and Breadth-First Search (BFS)—and a custom-developed algorithm using backtracking and obstacle avoidance. These algorithms aretested in a 20x20 grid-based simulated environment that mimics a typical lawn with obstacles, allowing a comparative analysis of their performance. **Genetic Algorithm (GA):** An optimization algorithm inspired by natural selection; GA is effective in exploring large solution spaces. Its strength lies in solving complex environments, though it may not always find the optimal path due to its stochastic nature and high computational demands. **Dijkstra's Algorithm:** A deterministic algorithm that guarantees the shortest path by systematicallyexploring all routes. While highly reliable, it can be computationally intensive, especially in large grids.



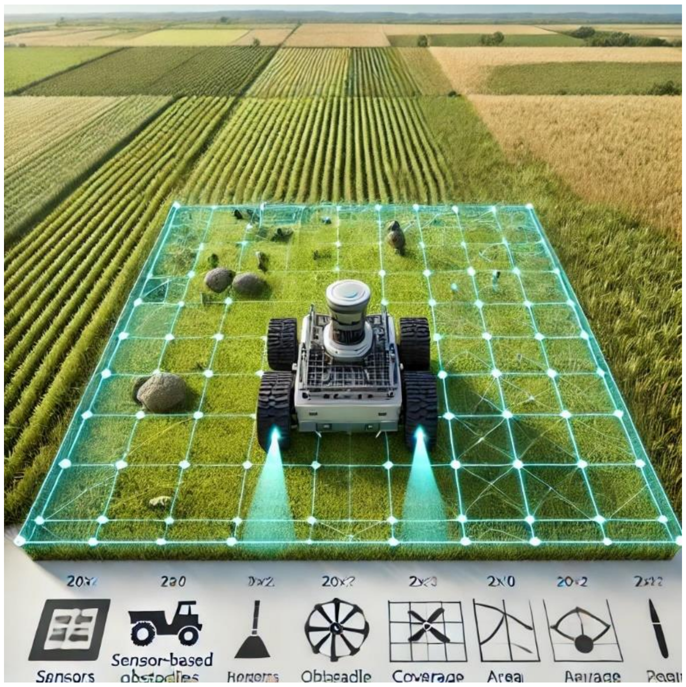
II. LITERATURE REVIEW

The field of autonomous systems has witnessed significant advancements over the past few decades, driven by the increasing demand for automation in sectors such as manufacturing, logistics, and home maintenance. Autonomous vehicles, including robotic lawn mowers, autonomous delivery vehicles, and autonomous mobile robots (AMRs), have become a focal point of research due to their potential to enhance efficiency, reduce labor costs, and improve operational safety. Central to the operation of these vehicles is the ability to navigate complex environments effectively, which relies heavily on the development and application of robust pathfinding algorithms.

2.1. Pathfinding Algorithms in Autonomous Systems

Pathfinding is a fundamental aspect of autonomous navigation, enabling robots to determine the most efficient route from a starting point to a destination while avoiding obstacles. The problem of pathfinding is well-studied within the broader fields of artificial intelligence and robotics, andvarious algorithms have been proposed and implemented over the years. Dijkstra's Algorithm, developed by Edsger.

Dijkstra in 1959, is one of the earliest and most well-known algorithms for finding the shortest path in a graph [1]. It operates by systematically exploring all possible paths in order to increase cost, ensuring that the first time a node is reached, it is via the shortest path. This algorithm has been widely adopted in various applications, particularly in network routing and robotics, due to its ability to guaranteethe optimal path. However, Dijkstra's Algorithm can be computationally intensive, especially when applied to large grids, as it requires the exploration of all nodes in the graph.



Building on the foundation of Dijkstra's Algorithm, Hart,Nilsson, and Raphael introduced the A* Pathfinding algorithm in 1968 [2]. A* improves upon Dijkstra's by incorporating a heuristic function that estimates the cost to reach the goal from any given node. This heuristic allows A* to focus its search on the most promising paths, reducingthe number of nodes that need to be explored and making it more efficient than Dijkstra's in many cases. A* is particularly well-suited for real time applications, where quick decision-making is essential, and has been widely used in gaming, robotics, and geographic information systems (GIS) [3]. Genetic Algorithms (GAs), inspired by the principles of natural selection and evolution, have also been applied to the problem of pathfinding. Introduced by John Holland in the 1970s [4], GAs operates by generating a population of potential solutions, evaluating their fitness, and iteratively refining them through processes analogous to genetic crossover and mutation. GAs are particularly effective in exploring large and complex solution spaces, making them well-suited for dynamic environments where the optimal path may not be immediately apparent. However, the stochastic nature of GAs means that they may not always find the absolute best path, and their computational demandscan be significant, particularly in environments where quick decisions are required [5]. Breadth-First Search (BFS) is another well-known pathfinding algorithm, notable for its simplicity and systematic approach. BFS explores all possible paths layer by layer, starting from the initial node and expanding outward [6]. In an unweighted grid, BFS guarantees the shortest path by exploring all nodes at the present depth before moving on to nodes at the next depth level. While BFS is straightforward and easy to implement, it can become inefficient in larger and more complex environments, where the number of nodes to be explored increases exponentially [7].

2.2. Applications of Pathfinding Algorithms in Autonomous Vehicles

The application of pathfinding algorithms in autonomous vehicles has been a subject of extensive research, particularly in the context of autonomous mobile robots (AMRs) and automated guided vehicles (AGVs). These vehicles are increasingly used in industrial settings, such as warehouses and manufacturing plants, where they navigate complex environments to transport goods, manage inventory, and perform other essential tasks [8].In the field of autonomous lawn mowers, the use of pathfinding algorithms is crucial for ensuring complete coverage of the lawn while avoiding obstacles. Early studies focused on simple navigation techniques, such as random movement and systematic coverage patterns, but these methods often resulted in inefficiencies, such as missed areas or over-mowing [9]. The introduction of more sophisticated pathfinding algorithms, such as A* and Dijkstra's, has significantly improved the performance of these robots, enabling them to navigate more effectively and optimize their mowing patterns [10].

For example, in the study by Zermas et al. [11], the authors explored the use of A* Pathfinding in an autonomous lawn mower designed for residential use. The algorithm was integrated with a sensor fusion system that combined data from GPS, ultrasonic sensors, and cameras to detect obstacles and map the environment. The results demonstrated that A* was able to efficiently navigate the lawn, avoiding obstacles and minimizing the time required to complete the mowing task. The study highlighted the importance of combining pathfinding algorithms with realtime sensor data to enhance the robot's adaptability to changing environmental conditions [12].

Similarly, in a study by Khatib et al. [13], Dijkstra's Algorithm was used to optimize the navigation of an autonomous snow blower. The algorithm was employed to calculate the shortest path through a grid-based representation of the snow-covered area, considering the vehicle's limitations in terms of speed and maneuverability. The study found that Dijkstra's Algorithm was effective in minimizing the time required to clear the area, but the computational demands of the algorithm were significant, particularly in larger environments [14].

Genetic Algorithms have also been explored in the context of autonomous navigation, particularly for environments where the optimal path is not easily determined. For instance, in a study by Michalewicz et al. [15], a GA was applied to the problem of pathfinding in a dynamic environment with moving obstacles. The algorithm was able to adapt to changes in the environment by continuously evolving the population of paths, leading to a more robust and flexible navigation strategy. However, thestudy also noted that the GA required significant computational resources, which could limit its applicabilityin real-time scenarios [16].

2.3. Sensor Fusion and Its Role in Pathfinding

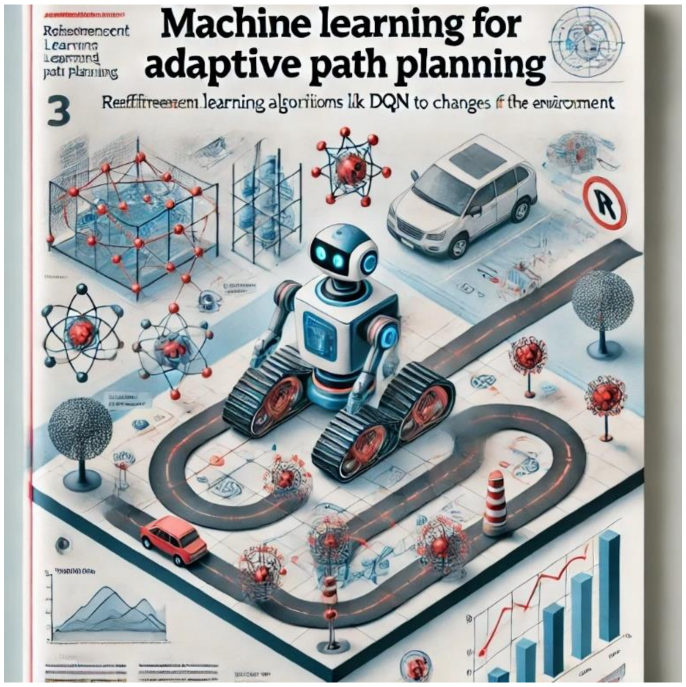
Sensor fusion is another critical component in the development of autonomous vehicles, including robotic lawn mowers. By combining data from multiple sensors, sensor fusion allows the robot to construct a more accurate representation of its environment, improving its ability to navigate and avoid obstacles [17]. Commonly used sensors in robo-mowers include GPS for positioning, ultrasonic sensors for detecting obstacles, and cameras for visual data [18]. The integration of sensor data with pathfinding algorithms enables more informed decision-making, enhancing the robot's ability to respond to dynamic changes in the environment [19].

Recent advancements in sensor fusion have focused on the use of machine learning techniques to improve theaccuracy and reliability of the fused data. For example, Takami et al. [20] explored the use of deep learning for sensor fusion in an agricultural robot, achieving significant improvements in obstacle detection and path planning. Similarly, Alonso et al. [21] applied a 1D convolutional neural network (CNN) for sensor data analysis in a robotic lawn mower, enabling real-time processing and improved navigation performance.

The combination of sensor fusion and advanced pathfinding algorithms represents a promising direction forthe future development of autonomous lawn mowers and other autonomous vehicles. By leveraging the strengths of both approaches, it is possible to create more efficient, reliable, and adaptable robots capable of performing complex tasks in dynamic environments [22].

2.4 Obstacle Avoidance in Robotic Pathfinding

The ability to efficiently detect and avoid obstacles is crucial in the design of autonomous robots, especially for applications such as grass-cutting in unstructured environments. Traditional approaches to obstacle avoidance often rely on sensors such as ultrasonic, infrared, or LiDAR, which provide real-time data on obstacles within the robot's path. Research by Kruse et al. [23] highlighted the effectiveness of combining multiple sensors and pathfinding algorithms to enhance an autonomous mower's adaptability. Their work demonstrated that a blend of A* and dynamic obstacle avoidance algorithms could adjust paths in real time, maintaining both speed and safety. While fixed obstacle configurations can be managed with pre-planned routes, autonomous systems operating in unpredictable outdoor environments benefit from adaptive algorithms that continuously process sensor inputs to dynamically adjust their path. This adaptability is vital for robotic lawn mowers operating in complex and obstacle-filled spaces, where obstacles like trees or garden fixtures are not always consistent or predictable.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2.5 Machine Learning for Adaptive Path Planning

Recent advancements in machine learning have introduced adaptive methods for path planning in dynamic environments. Reinforcement learning (RL) algorithms, such as Deep Q-Networks (DQNs) and Proximal Policy Optimization (PPO), allow robots to learn optimal paths over time based on trial and error, effectively adapting to new environments. Studies like those conducted by Zhu et al. [24] employed RL techniques in a simulated robotic mower, showing that after a training period, the mower could autonomously navigate obstacles more efficiently than traditional pathfinding methods. Unlike classical algorithms, these learning-based methods improve as they gather more data, gradually reducing computational time while optimizing energy consumption and task completion. Although RL-based approaches show promise in adapting to varied environments, their real-time application in robotic mowers remains limited by computational constraints, which necessitates further research into lightweight adaptive models.

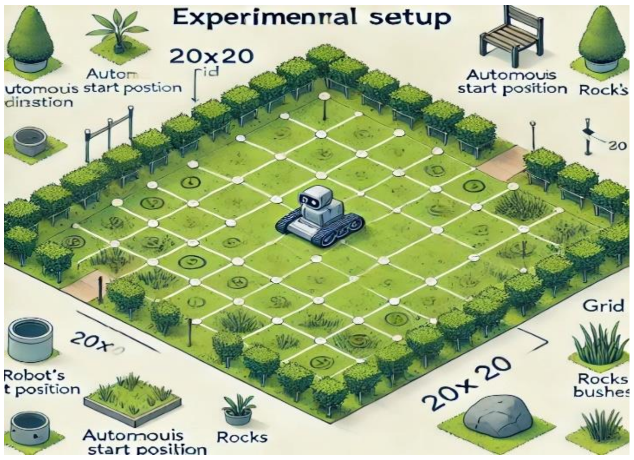
III. METHODOLOGY

This research aims to evaluate the performance of four well-known pathfinding algorithms—Genetic Algorithm (GA), Dijkstra's Algorithm, A* Pathfinding, and Breadth-First Search (BFS)—in the context of an autonomous grass-cutting robot. The methodology includes creating a simulated environment, implementing each algorithm, and analyzing performance metrics such as path length, computational time, and coverage efficiency. This section details the experimental setup, the algorithms used, and theprocedures followed to achieve the study's objectives.

3.1. Experimental Setup

The experimental setup involves a simulated 20x20 grid thatmimics a typical lawn environment. Obstacles such as trees and garden beds are randomly placed to represent real- world challenges faced by the grass-cutting robot.

1. **Grid Environment**: A 20x20 matrix, where each cell represents 1 square meter of lawn. Obstacles are placed randomly to cover approximately 20% of the grid.
2. **Robot Specifications**: The simulated robot has a cutting width of one cell and can detect obstacles in its immediate surroundings. Movement is restricted to four directions: up, down, left, and right, with each movement considered a singlestep.
3. **Obstacle Placement**: Obstacles are placed randomly at the beginning of each simulation run. The robot must navigate around them to reach a target position while ensuring complete coverage of the lawn.



3.2. Pathfinding Algorithms

The four pathfinding algorithms were implemented in Python and tested under identical conditions in the simulated environment. Each algorithm has unique advantages and challenges:

1. **Genetic Algorithm (GA)**: GA generates a population potential paths from the start to the target. Fitness is based on path length and proximity to obstacles. The algorithm iteratively refines paths through genetic crossover and mutation. In this study, GA uses a population of 50paths and runs for 100 generations with a 5%mutation rate.

$$\text{Fitness} = \frac{1}{\text{Path Length} + h(\text{goal})}$$

Where: h(goal) is the heuristic function, often the Manhattan distance $|x_{\text{goal}} - x| + |y_{\text{goal}} - y|$

For mutation and crossover, probabilities can be represented as:

$$P_{\text{mutation}} = 0.05$$

$$P_{\text{crossover}} = 0.7$$

2. **Dijkstra's Algorithm**: A deterministic algorithm that guarantees the shortest path by exploring all possible routes. It uses a priority queue to manage exploration but is computationally intensive.
The **shortest path** in Dijkstra's Algorithm is based on finding the minimal cumulative distance d(u,v) from the start node to each node in the graph:

$$d(u, v) = \min(d(u, v), d(u, w) + w(w, v))$$

Where:
d(u,v) represents the shortest path distance from node u to node v.
w(w,v) represents the weight of the edge between w and v.

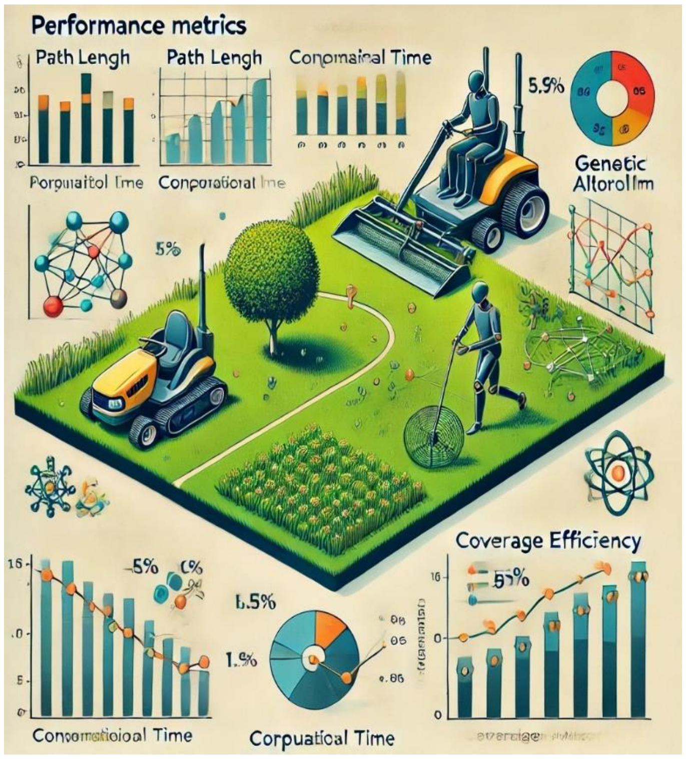
3. **A* Pathfinding**: Builds on Dijkstra's by incorporating a heuristic function to estimate the remaining cost to reach the target. This reduces the number of nodes explored. The Manhattan distance heuristic was used in this study due to the grid- based environment.
A* Algorithm optimizes the search by combining the path cost from the start node g(x) with a heuristic estimate h(x) of the remaining cost to the goal:

$$f(x) = g(x) + h(x)$$

Where:
g(x) is the known cost from the start to the current node.
h(x) is the heuristic cost estimate to the goal.

4. **Breadth-First Search (BFS)**: BFS explores all possible paths layer by layer, guaranteeing the shortest path in an unweighted grid. However, it can become inefficient in large grids with many obstacles. Breadth-First Search does not require a weighted path calculation, but it guarantees the shortest path in an unweighted grid by exploring nodes level by level. For pathfinding in an unweighted grid, the shortest path length d(u,v) is determined by the minimum number of steps:

$$d(u, v) = \min\{\text{steps from } u \text{ to } v\}$$



IV. PERFORMANCE METRICS

4.1. Simulation Process

Each algorithm was tested across 100 simulation runs, with different obstacle configurations for each run. The following performance metrics were measured:

1. **Path Length**: The total number of steps the robot takes to reach the target position.

$$L = \sum_{i=1}^{N} d(p_i, p_{i+1})$$

where Pi represents each point in the path and N is the number of points.

2. **Computational Time**: The time taken by the algorithm to calculate the path.

$$T = \int_{t_{\text{start}}}^{t_{\text{end}}} dt$$

3. **Coverage Efficiency**: The percentage of the grid area the robot successfully covers while navigating.

$$E = \frac{\text{Area Covered}}{\text{Total Area}} \times 100\%$$

4.2. Data Collection and Analysis

1. **Data Recording**: After each simulation, path length, computational time, and coverage efficiency were recorded.
2. **Statistical Analysis**: Descriptive statistics such as mean, median, and standard deviation were calculated.
3. **Comparison and Interpretation**: The results were compared to identify the strengths and weaknesses of each algorithm in balancing path length, computational time, and coverage efficiency.

4.3. Validation and Verification

1. **Validation of Simulation Environment**: The simulated environment was designed to accurately reflect real-world challenges faced by a robotic grass-cutting machine.
2. **Verification of Algorithm Implementations**: Algorithms were tested with known solutions to verify correctness.
3. **Sensitivity Analysis**: Changes in grid size, obstacle density, and robot specifications were tested to evaluate the robustness of each algorithm.

V. ALGORITHM IMPLEMENTATION,EVALUATION AND TESTING

5.1. GENETIC ALGORITHM PATHFINDING

The Genetic Algorithm (GA) is an optimization technique inspired by natural selection. It operates on a population of potential solutions, applying genetic operators such as selection, crossover, and mutation to evolvesolutions over generations.

1. **Initialization:** Create an initial population of random paths from the start to the goal. Each pathis generated by randomly selecting valid neighboring cells until the goal is reached or a maximum path length is exceeded.
2. **Selection:** Evaluate the fitness of each path based on its length and proximity to the goal. Select the fittest paths for

reproduction. The fitness function in this context is defined as the sum of the path length and the heuristic distance (Manhattandistance) to the goal.

3. **Crossover:** Combine pairs of selected paths to create offspring paths. This is done by selecting a crossover point and combining segments of the parent paths.
4. **Mutation:** Introduce random changes to some paths to maintain genetic diversity. This involves selecting a random point in the path and replacing it with a valid neighboring cell.
5. **Iteration:** Repeat the selection, crossover, and mutation steps for a set number of generations or until convergence, i.e., when the population does not show significant improvement.

IMPLEMENTATION

Fitness Function: Combines the path length and the heuristic distance to the goal.
Generations: The algorithm iterates over multiple generations to improve the population of paths.
Population Management: Maintains a populationof paths, selecting the best ones for reproduction, and
introducing variations to explore the solution space
Mathematical Representation
The algorithm iteratively refines paths through genetic crossover and mutation. In this study, GA uses a population of 50 paths and runs for 100 generations with a 5%mutation rate.

$$\text{Fitness} = \frac{1}{\text{Path Length} + h(\text{goal})}$$

Where: h(goal) is the heuristic function, often the

Manhattan distance $|x_{\text{goal}} - x| + |y_{\text{goal}} - y|$

For mutation and crossover, probabilities can be represented as:

$$P_{\text{mutation}} = 0.05$$

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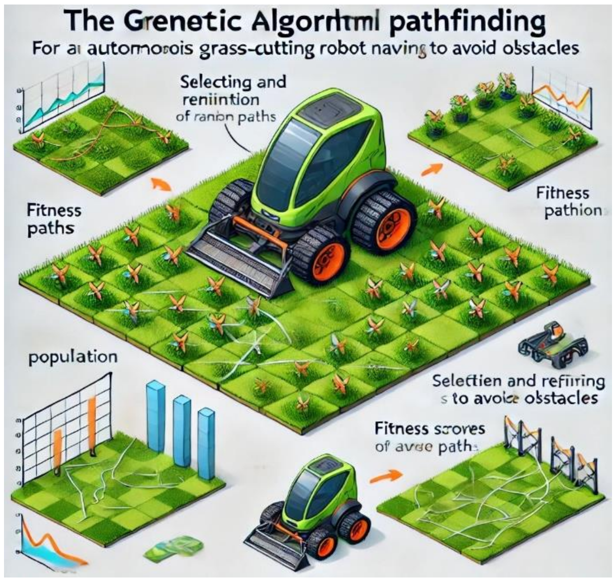
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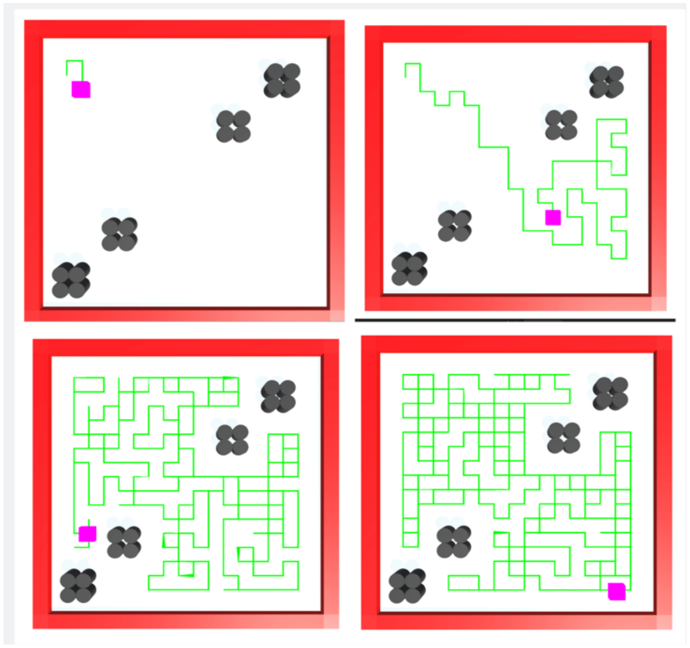
RESULTS

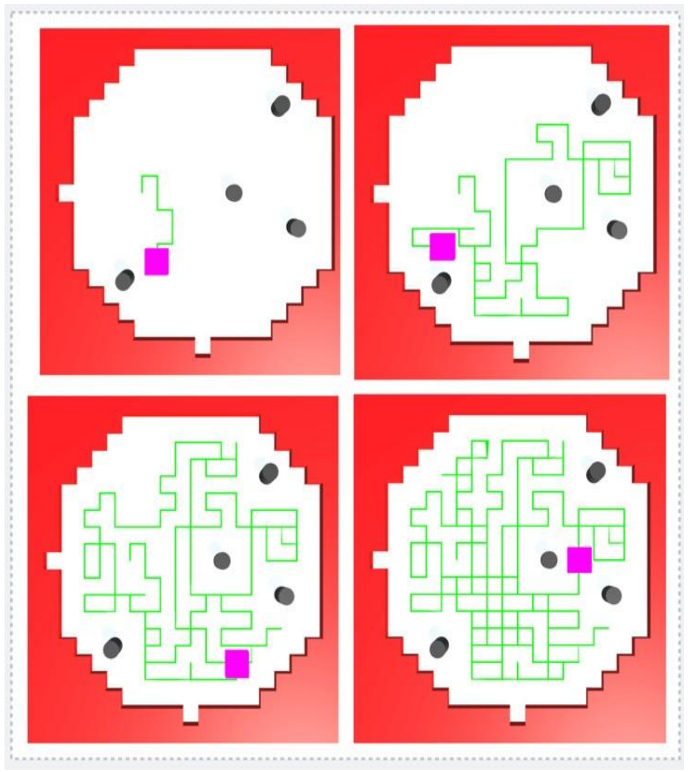
- **Path Length:** 351
- **Time Required:** 149sec



SAME ALGORITHM WITH DIFFERENT MAP REPRESENTATION

RESULTS

- **Path Length:** 387
- **Time Required:** 173sec



5.2. DIJKSTRA'S ALGORITHM

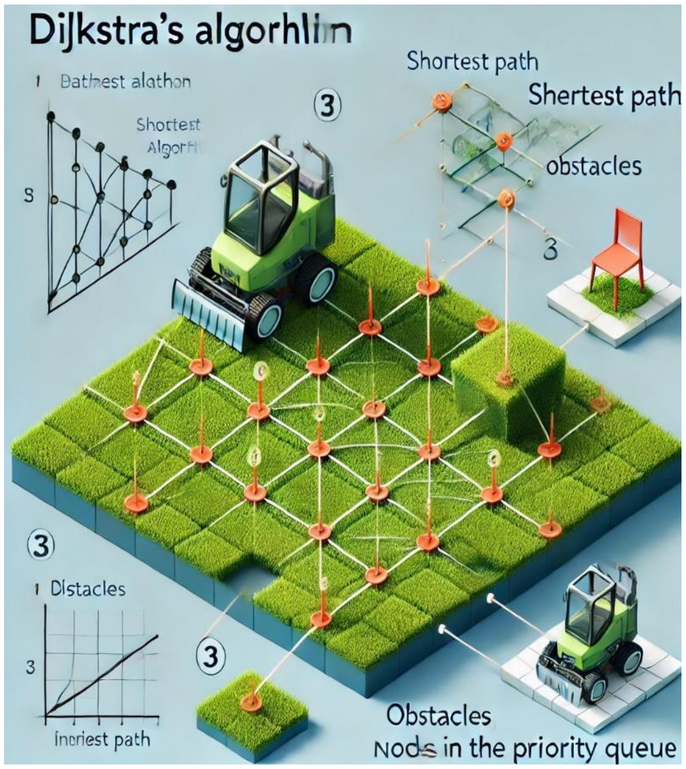
Logic: Dijkstra's Algorithm is a classic graph-based algorithm that finds the shortest path between nodes in a weighted graph. It systematically explores paths inorder to increase cost.

Initialization: Set the distance to the start node to zero and all other nodes to infinity.Add the start node to a priority queue.

Exploration: Remove the node with the smallest distance from the queue and updatethe distances to its neighbors.

Relaxation: If a shorter path to a neighbor is found, update its distance and add it to the queue.

Termination: Repeat until the goal node isreached or the queue is empty.



IMPLEMENTATION

Priority Queue: Uses a priority queue to ensure the smallest distance node is processed first.

Shortest Path Guarantee: Guarantees the shortest path in an unweighted grid by exploring nodes in order to increase distance.

MATHEMATICAL REPRESENTATION

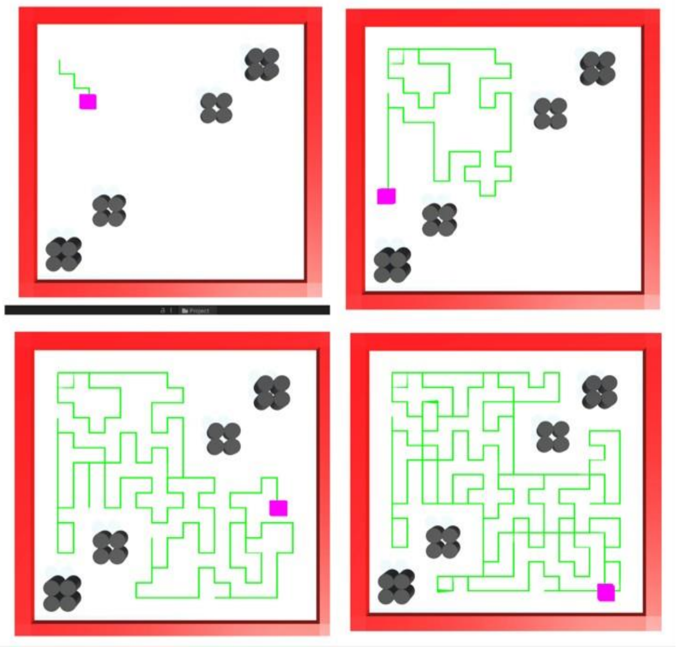
The **shortest path** in Dijkstra's Algorithm is based on finding the minimal cumulative distance d(u,v) from the start node to each node in the graph:

$$d(u,v) = \min(d(u,v), d(u,w) + w(w,v))$$

Where:

d(u,v) represents the shortest path distance from node u to node v.

w(w,v) represents the weight of the edge between w and v.



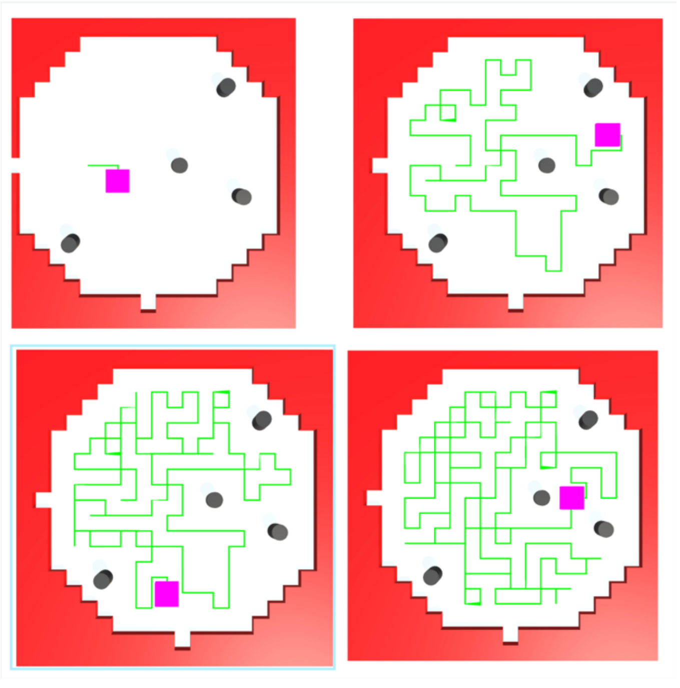
RESULTS

- **Path Length:** 285 units
- **Time Required:** 131sec

SAME ALGORITHM WITH DIFFERENT MAP REPRESENTATION

RESULTS

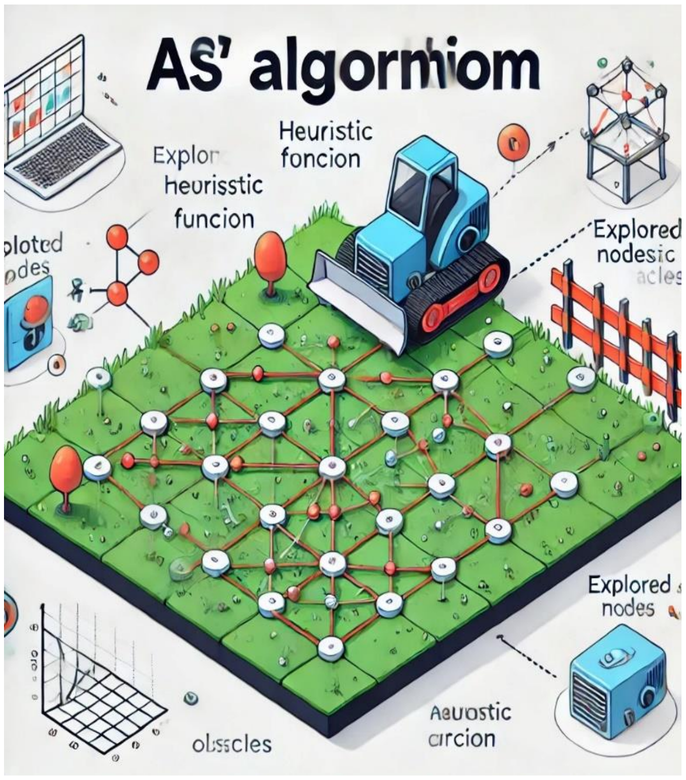
- **Path Length:** 220 units
- **Time Required:** 98sec



5.3. A* PATHFINDING

A* Pathfinding combines the benefits of Dijkstra's Algorithm with a heuristic function to estimate the cost toreach the goal, making it more

efficient for many problems.
Initialization: Set the distance to the start node tozero and all other nodes to infinity. Add the start node to a priority queue with a priority equal to the heuristic estimate to the goal.
Exploration: Remove the node with the lowesttotal cost (distance + heuristic) from the queue and update the distances to its neighbors.
Relaxation: If a shorter path to a neighbor is found, update its distance and add it to the queuewith the new total cost.
Termination: Repeat until the goal node isreached or the queue is empty.



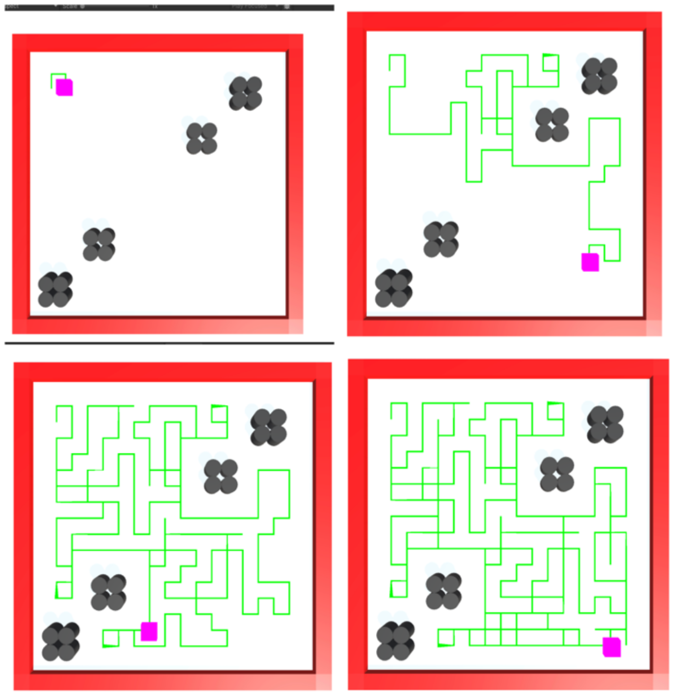
IMPLEMENTATION:
Combined Cost: Combines the actual distance from the start with a heuristic estimate to the goal.
Priority Queue: Uses a priority queue to efficiently find the path with the lowest estimatedtotal cost.

MATHEMATICAL REPRESENTATION:
A* Algorithm optimizes the search by combining the path cost from the start node g(x) with a heuristic estimate h(x) of the remaining cost to the goal:

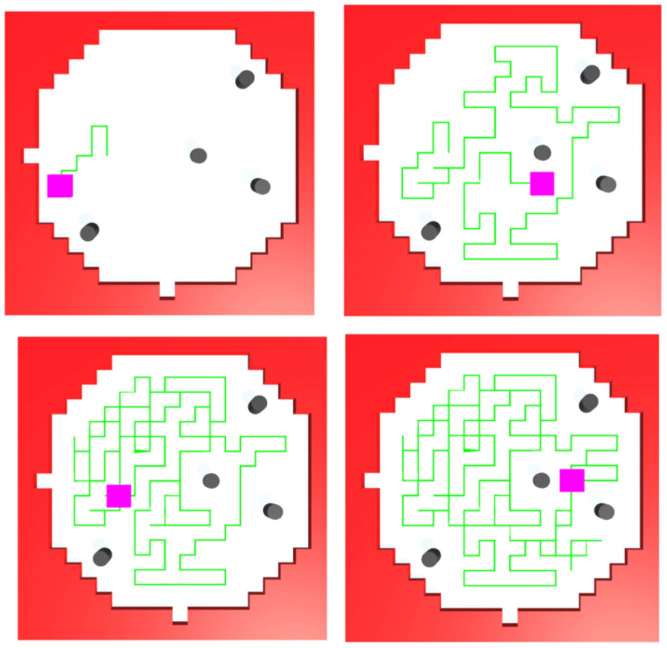
$$f(x) = g(x) + h(x)$$

Where:
g(x) is the known cost from the start to the current node.
h(x) is the heuristic cost estimate to the goal.

RESULTS
- **Path Length:** 303 units
- **Time Required**: 136



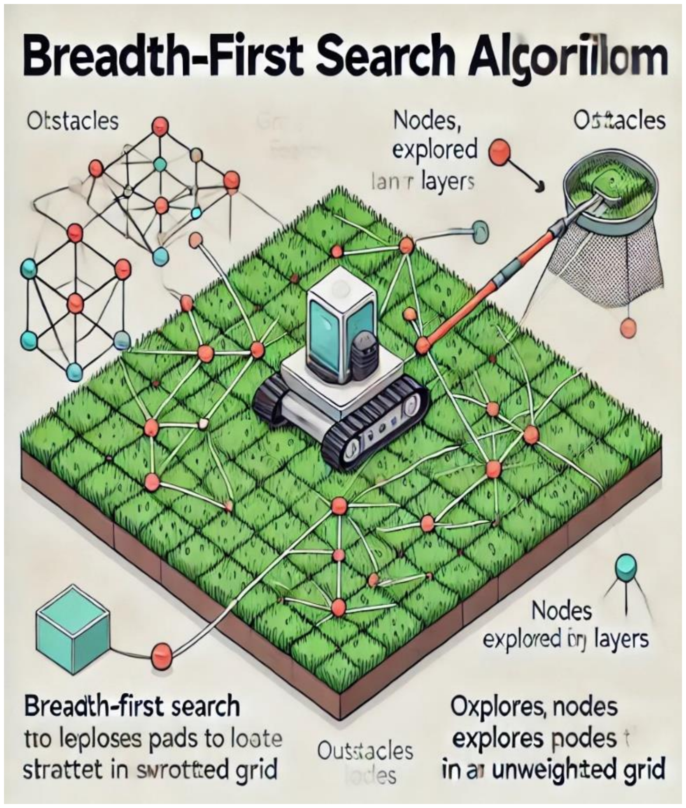
SAME ALGORITHM WITH DIFFERENT MAP REPRESENTATION



5.4. BREADTH-FIRST SEARCH (BFS)

Logic: Breadth-First Search (BFS) systematically exploresall possible paths in a level-by-level manner, ensuring the discovery of the shortest path in an unweighted grid. This method is particularly effective for simple grid layouts where all moves carry equal cost.
Steps Involved:
Initialization:
Start Node: Begin with adding the startnode to a queue.

Visited Mark: Mark the start node as visited to prevent reprocessing.
Exploration:
Node Removal: Remove the node at thefront of the queue.
Neighbor Addition: Add all unvisited adjacent nodes to the queue and mark them as visited.
Termination:
The process repeats until either the goal node is reached, or the queue becomes empty, indicating that all possible paths have been explored.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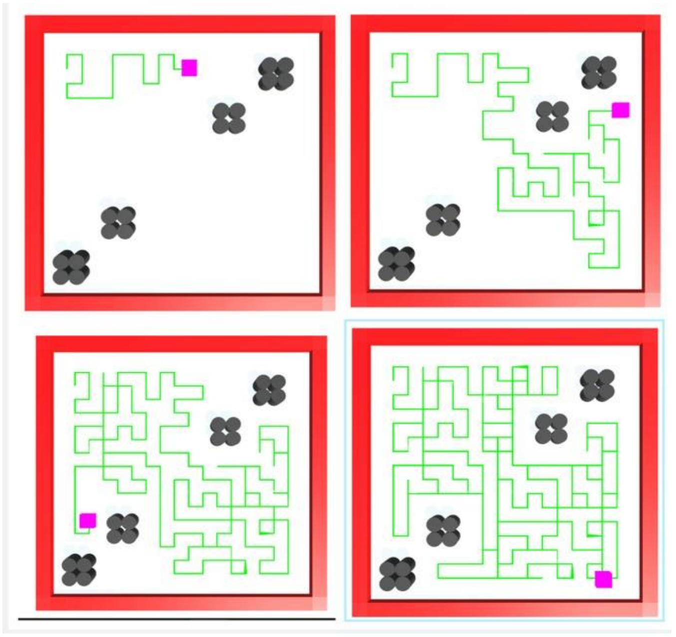
IMPLEMENTATION
Queue Utilization: BFS uses a queue to manage the nodes in the order they were discovered, facilitating level-order traversal
Shortest Path Assurance: By exploring nodes in their discovery order and ensuring all possible paths are considered, BFS guarantees the shortestpath in unweighted grids

MATHEMATICAL REPRESENTATION
Breadth-First Search does not require a weighted path calculation, but it guarantees the shortest path in an unweighted grid by exploring nodes level by level. For pathfinding in an unweighted grid, the shortest path length d(u,v) is determined by the minimum number of steps:

$$d(u,v) = \min\{\text{steps from } u \text{ to } v\}$$

RESULTS
- **Path Length:** 312 units
- **Time Required:** 141



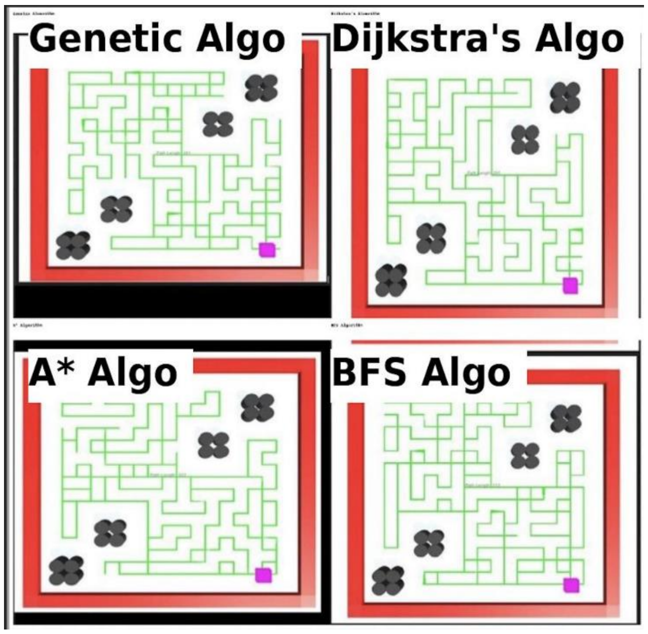
SAME ALGORITHM WITH DIFFERENT MAP REPRESENTTION
- **Results: Path Length:** 220
- **Time Required:** 98sec

VI. ADDITIONAL WORK ON ALGORITHMS

Enhanced A* Algorithm in Orchards: A*
Research from Qingdao University focuses on an improved A* algorithm tailored for navigating robotic mowers in orchards. This involves refining the algorithm to reduce the number of turns and improve speed, adapting it specifically for structured agricultural environments. This modified A* algorithm leverages grid-based mapping and robot cluster traversal to optimize path.
Voronoi-based Rapid Coverage Path Planning:
A novel approach incorporates the Voronoi diagram to create efficient coverage path plans for robotic mowers in irregular environments. This method utilizes a Boustrophedon motion planning strategy combined with Voronoi partitions to minimize redundant movements and ensure complete area coverage. It's designed to handle the unique challenges posed by outdoor spaces that are not uniformly structured.

VII. RESULTS AND COMPARISON

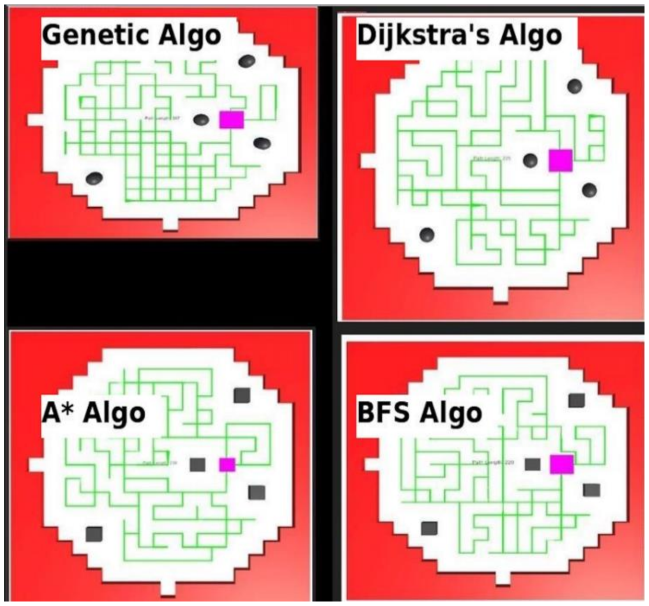
Algorithm	Path Length (units)	Time Required (seconds)
Genetic Algorithm	345	146
Dijkstra's Algorithm	291	131
A* Pathfinding	303	133
Breadth-First Search	312	139



5.2. RESULTS AND COMPARISON FOR CIRCULAR MAP

The table below summarizes the results of each algorithm:

Algorithm	Path Length (units)	Time Required (seconds)
Genetic Algorithm	345	146
Dijkstra's Algorithm	291	131
A* Pathfinding	303	133
Breadth-First Search	312	139



VIII. RESULTS

The comparative analysis of pathfinding algorithms for an autonomous grass-cutting robot highlights the strengths and trade-offs associated with each approach. Dijkstra's Algorithm consistently guarantees the shortest path and demonstrates high reliability in finding optimal paths. However, its computational intensity can be a drawback, especially for real-time applications. A* Pathfinding strikes a balance between path optimality and computational efficiency by incorporating heuristic guidance, making it suitable for real-time autonomous systems that require quick decision-making. Breadth-First Search (BFS), although simple and effective in unweighted grids, becomes inefficient in larger, more complex environments. The Genetic Algorithm, with its ability to explore a wide range of potential solutions, proves valuable in more dynamic and complex scenarios, albeit at the cost of increased computational resources.

For the specific case of an autonomous grass-cutting robot navigating a grid with obstacles, Dijkstra's Algorithm is ideal for ensuring full coverage and minimal path length, whereas A* is a strong candidate for real-time navigation due to its balance of speed and efficiency. The insights gained from this study will be crucial in designing more effective autonomous lawnmowers, as they provide a clear understanding of the algorithms' applicability based on the complexity of the environment and the robot's operational constraints. Further research can focus on hybrid approaches that combine the strengths of multiple algorithms or explore machine learning-based methods for adaptive pathfinding in real-world scenarios.

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