A HYBRID DEEP LEARNING-BASED PATH-PLANNING ALGORITHM FOR MULTIFUNCTIONAL MANIPULATOR-TYPE DISINFECTION ROBOT

DR. KOVVURI N BHARGAVI[1*], TANAYA GANGULY[2], MANOJ KUMAR PADHI[3], DR.G. JOSE MOSES[4], DR. NIRAJ KUMAR[5], NAGENDAR YAMSANI[6]

[1*]Associate Professor&HOD,Department of CSE-AIM, Aditya University,India
[2]Assistant Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram-522302, Guntur,Andhra Pradesh, India
[3]Assistant professor,Department of Computer Science & Engineering,Centurion University Of Technology And Management,Paralakhemundi,Odisha, India
[4]Professor of CSE,School of Engineering,Malla Reddy University,Hyderabad-500100Telangana, India
[5]Associate Professor,Department of Electronics and communication Engineering, UIET University,C.S.J.M University ,KANPUR , INDIA
[6]Assistant Professor, School of Computer Science and Artificial Intelligence, SR University, Warangal, Telangana, India
[1*]Corresponding author email: bhargavikovvri@gmail.com

ABSTRACT

This research focuses on developing an advanced path-planning algorithm for a multifunctional manipulator-type disinfection robot, incorporating deep learning techniques to optimize its operational efficiency and adaptability. Moreover, these robots are used to disinfect surfaces in sensitive environments, such as public facilities, laboratories, and hospitals. However, optimizing the performance of robots is challenges because energy usage, and disinfection coverage time can make dynamic environments and navigating difficult. Also, arm co-ordination and obstacle avoidance do not provide effective disinfection due to the changing criteria. To overcome these issues, the developed study reveals that the hybrid solution which is the integration of Deep learning (DL) frameworks and path planning strategies enhances efficiency as well as adaptability. The study's objective is to address the limitations of traditional algorithms, like A* and Dijkstra's, which fail in dynamic environments such as hospitals where obstacles are constantly changing. Moreover, the developed algorithm finds the better route from the starting location of robot to the robot target while considering the difficulty and map structures. To overcome these limitations, a hybrid model is proposed, combining the A* algorithm for global path planning with Proximal Policy Optimization (PPO), a deep reinforcement learning method for real-time path adjustments. The methodology involves training the robot in simulated environments and testing it in real-world settings such as hospitals. Results show significant improvements in path efficiency, energy consumption, and collision avoidance, with the proposed algorithm achieving 98.5% coverage efficiency. The implications of this research highlight the potential of deep learning to enhance the adaptability and effectiveness of disinfection robots, especially in dynamic, high-traffic environments, ensuring thorough sanitation and minimizing energy usage.

Keywords: *Path Planning, Deep Reinforcement Learning, Disinfection Robots, A* Algorithm, Proximal Policy Optimization.*

1. INTRODUCTION

A. Background on Disinfection Robots

The emergence of disinfection robots has gained significant attention in recent years, especially in the wake of global health crises such as the COVID-19 pandemic. These robots are designed to autonomously navigate through environments such as hospitals, airports, and public spaces to disinfect surfaces using various technologies like ultraviolet (UV) light or chemical sprays. Unlike traditional disinfection methods that rely on human labor, disinfection robots can operate continuously and efficiently, minimizing human exposure to pathogens. Their implementation in healthcare and public facilities has proven to be an effective way to enhance sanitation standards and reduce the spread of infectious diseases [1]. The need for such robots is particularly pressing in high-risk environments where the frequency and thoroughness of disinfection must be maintained to prevent cross-contamination. As these robots become more prevalent, advancements in their autonomy, navigation, and efficiency are key to optimizing their deployment [2].

B. Importance of Path Planning and Deep Learning

Path planning is one of the critical components that determine the efficiency and effectiveness of disinfection robots. The ability of a robot to plan an optimal path through an environment ensures comprehensive disinfection while minimizing time and energy consumption. In dynamic environments such as hospitals, where obstacles and human presence are constantly changing, robust path planning is essential. Traditional algorithms like A* and Dijkstra's algorithm have been used for path planning, but they often fall short in complex, unstructured environments [3]. Here, deep learning methods provide a significant advantage. By utilizing neural networks, deep learning models can enable robots to learn from the environment, anticipate obstacles, and adapt to dynamic conditions, leading to more intelligent navigation strategies [4].

The integration of deep learning in path planning allows disinfection robots to go beyond predefined routes, learning and improving over time. This approach enables real-time decision-making, where the robot can dynamically adjust its path based on new information, making it more effective in ensuring complete disinfection coverage. Furthermore, deep learning models such as convolutional neural networks (CNNs) and reinforcement learning techniques have been increasingly applied to enhance the robot's navigation capabilities in cluttered and uncertain environments [5]. The combination of deep learning with traditional path-planning approaches offers a hybrid model that not only ensures optimal routes but also accounts for environmental changes in real time. This is particularly crucial for disinfection robots operating in healthcare environments where human interaction and unforeseen obstacles can significantly alter the navigation landscape.

C. Research problem and goals

The primary challenge faced by disinfection robots in complex and dynamic environments is the inefficiency of current path-planning algorithms. Traditional methods, such as A* and Dijkstra's, are effective in static settings but struggle to adapt to environments with constant changes, such as those involving human movement or shifting obstacles. These algorithms often fail to ensure full coverage of the area, leading to missed spots and incomplete disinfection, which can result in potential health risks, especially in high-stakes environments like hospitals or public spaces. Additionally, existing robots may not efficiently adapt to real-time changes, limiting their effectiveness. While deep learning techniques have shown promise in robotics navigation, their application to path planning for disinfection robots remains underexplored. Thus, there is a need for advanced algorithms that incorporate deep learning to improve both adaptability and efficiency in these dynamic settings.

The goal of this research is to develop an advanced path planning algorithm for multifunctional manipulator-type disinfection robots that leverages deep learning to optimize efficiency and adaptability. The primary objectives include creating a deep learning-based model capable of adjusting the robot's path in real time to account for dynamic obstacles and environmental changes. This research will focus on optimizing the robot's path to ensure comprehensive disinfection coverage, minimizing both time and energy consumption while ensuring no areas are missed. Additionally, the algorithm will aim to enhance the robot's ability to adapt to real-time changes in the environment, such as moving people or objects, without compromising its disinfection process. Ultimately, the developed algorithm will be tested in real-world environments to validate its effectiveness in improving the overall performance of disinfection robots in ensuring thorough sanitation in dynamic and complex settings.

2. RELATED WORK

A. Overview of Existing Path Planning Algorithms (Extended)

Path planning algorithms have long been a focal point of robotics research, where the primary goal is to ensure that a robot can efficiently navigate an environment without collisions. The classical algorithms include A*, Dijkstra's algorithm, and the family of Rapidly-Exploring Random Trees (RRTs). Beyond these, *Potential Field* methods have been explored, where a robot is treated as a particle moving in a potential field generated by goals and obstacles. This method was popularized for its simplicity but often suffered from issues such as local minima, where the robot could get stuck in non-optimal locations without reaching its goal [6]. Similarly, *Voronoi Diagrams* and *Cell Decomposition* are also classical methods used for

Journal of Theoretical and Applied Information Technology
15th March 2026. Vol.104. No.5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

path planning. While they provide comprehensive coverage of the environment, these methods typically require high computational resources, making them less practical for real-time or dynamic scenarios [7].
In dynamic and uncertain environments, algorithms like *Dynamic Window Approach (DWA)* and *Artificial Potential Fields (APF)* have been applied to handle real-time obstacle avoidance. However, these methods still fall short when faced with the need for adaptive, learning-based solutions that can deal with unstructured and dynamic spaces. Algorithms like *Fast Marching Method (FMM)* and *Optimal Rapidly-Exploring Random Trees (RRT)** improve the efficiency and convergence of path planning, but they still require significant computational overhead, which may be impractical for real-time navigation in rapidly changing environments [8].
The limitations of these traditional algorithms, particularly their inability to adapt to changing environments without manual intervention, highlight the need for more intelligent systems.

B. Deep Learning Applications in Robotics

Deep learning has revolutionized many areas of robotics, particularly in vision, perception, and path planning. One major application area is object detection and semantic mapping, where Convolutional Neural Networks (CNNs) have been employed to help robots interpret their environment through images. CNN-based models like YOLO (You Only Look Once) and Faster R-CNN have enabled robots to detect and classify objects in real-time, which is essential for efficient navigation in unstructured environments [9]. Furthermore, deep learning enables robots to engage in more complex decision-making processes. For instance, by combining deep learning with sensor fusion, a robot can merge data from multiple sensors (e.g., LiDAR, RGB-D cameras) to create a more accurate and detailed map of its surroundings, allowing for more informed path planning decisions [10].
A breakthrough in deep learning applications to path planning is seen in the use of *Deep Reinforcement Learning (DRL)*. DRL merges the principles of reinforcement learning, where an agent learns from interactions with its environment, with deep neural networks to handle complex, high-dimensional state spaces. Notably, algorithms like *Deep Q-Networks (DQN)*, *Asynchronous Advantage Actor-Critic (A3C)*, and *Proximal Policy Optimization (PPO)* have been applied in scenarios where the robot learns optimal navigation strategies by receiving feedback (rewards or penalties) based on the success of its actions. This adaptive learning capability is critical for path planning in unpredictable environments, such as hospitals or public spaces, where human movement and obstacles are constantly changing [11].
One of the key benefits of DRL is its ability to handle complex, multi-agent environments, which is particularly useful for swarm robotics and autonomous vehicles. In these scenarios, each agent (robot) learns not only to navigate but also to coordinate with other agents, thereby avoiding collisions and optimizing group efficiency. DRL has been applied to problems such as autonomous driving, where it helps cars navigate urban environments while obeying traffic rules and avoiding pedestrians [12]. In addition to navigation, DRL has also been used in manipulation tasks where robots need to interact with objects in their environment, such as in warehouse automation or surgical robotics, highlighting its versatility across robotic applications.
In the context of disinfection robots, combining DRL with CNNs and sensor fusion allows for real-time adaptability, enabling the robot to navigate highly dynamic environments. Unlike traditional path planning algorithms, which rely on predefined maps or rules, DRL-equipped robots can learn to navigate based on their experiences, making them highly effective in environments that change over time, such as hospitals or public buildings.
Another significant deep learning approach applied in robotic path planning is *Generative Adversarial Networks (GANs)*. GANs have been used to generate synthetic environments in which robots can train their navigation policies without the need for extensive real-world trials. This helps in training robots in a variety of simulated environments, thereby improving their adaptability when deployed in real-world scenarios [13]. Similarly, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been applied to path planning by predicting future states of the environment, which is crucial in dynamic settings where obstacles move unpredictably [14].

C. Challenges and Future Directions

Despite the advances in deep learning applications for robotic path planning, several challenges remain. One of the primary issues is the interpretability of deep learning models. These models, particularly deep reinforcement learning, are often considered "black boxes," making it difficult to understand the reasoning behind certain decisions. This lack of transparency can be problematic, especially in safety-critical applications like healthcare, where trust in the robot's decisions is crucial. Additionally, deep learning models require vast amounts of training data and computational resources, which can be impractical for real-time applications or environments where data is scarce.

Another challenge is the generalization of deep learning models across different environments. While deep learning models can adapt to new environments, they may still struggle when confronted with situations that significantly differ from the data they were trained on. Research into transfer learning and domain adaptation aims to address this issue by enabling models to generalize better across various settings. Furthermore, combining traditional path-planning algorithms with deep learning techniques in hybrid models could offer a promising approach by leveraging the strengths of both methods.

Here, this study proposes an integrated strategy that hybrids the A* algorithm with the PPO replica. Consequently, difference to previous studies that only use conventional path-planning strategies like Dijkstra's, A*, CNN, RNN, LSTM, etc these are performs poorly in unpredictable, dynamic settings, and use deep reinforcement learning techniques alone. Moreover, these traditional algorithms have poor global optimization as well as high training overhead. In the concern of real-world disposition restrictions contains dynamic human traffic, shifting barrier configurations and asymmetrical room layouts in hospitals which a are regularly ignored in earlier publications. This study demonstrates better performance for achieving finest coverage efficiency and condensed energy usage. This performance is not normally described in comparable prevailing schemes by integrating simulation-driven training process with respect to the real-world testing concerns, in addition to confirming algorithmic robustness and effectiveness.

D. Research Hypothesis

(i) How the hybrid approaches are outperforming the conventional methods based on their learning capabilities?

Traditional path planning strategies has no priorities and does not have changing layouts, but the proposed integrated model has AI with path panning ability in real-world environments.

(ii) Why the key parameters are indicates the healthcare managements for the safety authorities?

The developed research can contribute the public health efforts during the epidemics so the autonomous disinfection control is important

3. METHODOLOGY

A. *Robot Hardware Specifications*

The disinfection robot utilized in this study is a multifunctional manipulator-type robot, equipped with advanced hardware to ensure effective disinfection and autonomous navigation. The robot features a six-axis robotic arm that is capable of performing a wide range of movements, allowing for precise and comprehensive surface disinfection. The robotic arm is fitted with both UV-C lamps and a nozzle for chemical spraying, making it versatile for different types of disinfection tasks. Additionally, the robot is equipped with a high-resolution LiDAR sensor, RGB-D cameras, and ultrasonic sensors to ensure accurate real-time perception of its environment. These sensors provide 3D mapping capabilities and obstacle detection, which are critical for safe and efficient navigation in complex environments like hospitals or public spaces. The robot is also powered by a lithium-ion battery that allows for continuous operation for up to 8 hours, ensuring long-duration disinfection tasks without frequent recharging. An onboard computer system with a GPU (e.g., NVIDIA Jetson Xavier) is used to process sensor data and execute the deep learning-based path planning algorithms in real time.

B. *Algorithm Design and Deep Learning Model Used*

The path-planning algorithm for this disinfection robot is based on a hybrid approach that combines traditional path planning with deep learning. The algorithm integrates a modified version of the A* algorithm for global path planning and a deep reinforcement learning (DRL) model for real-time, adaptive local navigation. The A* algorithm is responsible for generating an initial global path that covers the entire area to be disinfected, ensuring that the robot moves optimally to cover all surfaces without significant overlaps or missed areas. However, the A* algorithm alone cannot handle dynamic obstacles or real-time environmental changes.

To address this limitation, the deep learning component, based on a Proximal Policy Optimization (PPO) reinforcement learning

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

model, is used for local path adjustments. The PPO model is chosen for its balance between exploration and exploitation, making it well-suited for environments with unpredictable dynamics. The deep reinforcement learning model continuously receives input from the robot's sensors (LiDAR, cameras) and learns optimal navigation strategies by interacting with the environment. The robot's movements are guided by a reward function that penalizes collisions and missed areas while rewarding efficient and complete disinfection coverage. This allows the robot to adjust its path in real time, avoiding obstacles like people or equipment, while still adhering to the overall disinfection strategy determined by the A* algorithm.

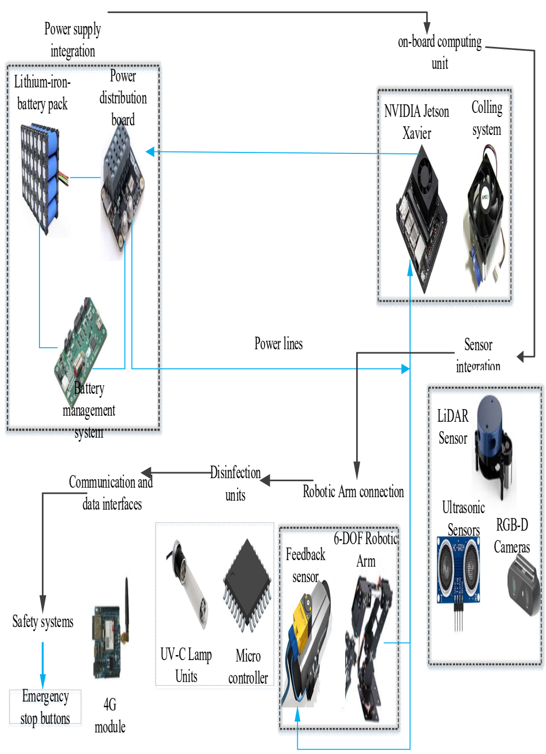

Figure.1 Schematic Representation Of Proposed Model

To enhance the efficiency of the learning process, the model uses convolutional neural networks (CNNs) to process visual data from the RGB-D camera. The CNN extracts feature such as obstacles, free space, and surface types, which are then fed into the reinforcement learning model. The combination of the A* algorithm for global planning and PPO for local real-time adaptation ensures that the robot can operate effectively in both static and dynamic environments.

C. *Training Data and Environment*

The deep learning model used for real-time path adjustment was trained using both simulated and real-world environments. Initially, the robot was trained in a simulated environment created using the Robot Operating System (ROS) and Gazebo simulator. The simulation environment replicates real-world hospital settings, including hallways, patient rooms, and various obstacles such as beds, chairs, and medical equipment. The simulated environment was varied to include both static and dynamic elements, such as moving people, to ensure the model can adapt to real-world conditions.

For training, a combination of reinforcement learning techniques was employed. The robot interacted with the environment, receiving feedback based on its actions. Positive rewards were given for actions that led to efficient path coverage and successful disinfection, while negative rewards were assigned for collisions, unnecessary path overlaps, or missed areas. This training process continued through thousands of episodes, allowing the model to learn optimal navigation strategies through trial and error.

After the initial training in the simulated environment, the model was fine-tuned in real-world settings, including hospitals and public spaces, to ensure its adaptability to varying conditions. Real-world training involved deploying the robot in dynamic environments where human movement and changes in the arrangement of objects were common. The robot was continuously monitored, and the model was retrained using real-time feedback to improve its performance in these environments. This fine-tuning process ensured that the robot could effectively navigate and disinfect complex spaces while adapting to changes in real-time.

D. *Proposed Path Planning Algorithm*

Algorithm Architecture

The proposed path planning algorithm is a hybrid architecture combining traditional path planning methods with advanced deep learning techniques, specifically designed for multifunctional manipulator-type disinfection robots. The architecture is divided into two key components:

Global Path Planning and **Local Path Adjustment**.

- **Global Path Planning**: At the core of the global path planning stage is the A* algorithm. This component is responsible for generating an initial route that ensures full coverage of the disinfection area. A* uses a heuristic approach to compute the shortest possible path that covers all necessary areas, taking into account static obstacles like walls, furniture, and other fixed structures. The output is a series of waypoints that guide the robot through the environment in an efficient manner, ensuring minimal overlap and maximum coverage.

- **Local Path Adjustment**: The local path adjustment relies on a **Proximal Policy Optimization (PPO)** deep reinforcement learning model. This component works in parallel with the global path planner and is responsible for dynamically adjusting the robot's path based on real-time environmental inputs. Using sensory data from LiDAR and RGB-D cameras, the PPO model can detect moving obstacles, such as people or equipment, and make real-time decisions to navigate around them. The architecture also incorporates a **Convolutional Neural Network (CNN)** to process visual data and extract essential features like obstacles, surface boundaries, and floor layout.

The hybrid model allows for a layered approach where the global path planner ensures comprehensive coverage, while the deep learning model adapts the path in real-time to handle dynamic elements. Both components are integrated into a central decision-making module, which ensures the robot can transition smoothly between global planning and local adjustments.

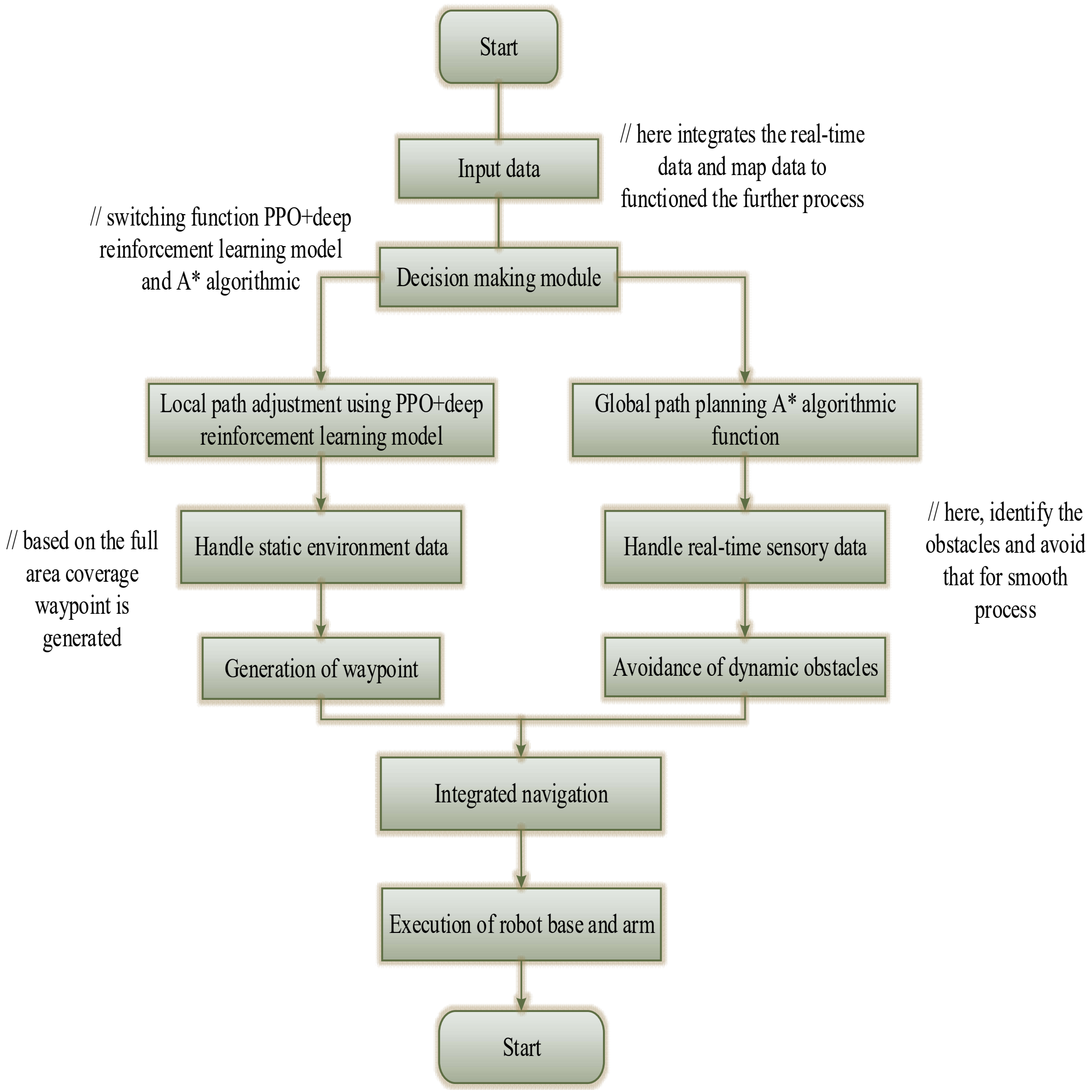

Figure.2 Flow of proposed algorithm

E. Implementation Steps

The implementation of the proposed algorithm follows a structured approach, detailed in the steps below:

- **Mapping the Environment**: The first step involves mapping the environment using the robot's sensors (LiDAR and RGB-D cameras). The sensor data is processed to create a detailed 3D map of the area, identifying static obstacles such as walls, furniture, and other permanent structures.
- **Global Path Generation**: Once the environment is mapped, the A* algorithm is applied to generate an optimal global path. This path is designed to ensure complete disinfection coverage of the target area, considering static obstacles. A grid-based map is created, where each cell represents a small segment of the environment, and the A* algorithm computes the optimal route through this grid.
- **Integration with Deep Learning**: As the robot begins executing the global path, the deep reinforcement learning (PPO) model is activated. The model takes continuous input from the robot's sensors, processing real-time data on dynamic obstacles. The CNN embedded in the architecture processes visual data, identifying objects, obstacles, and available paths. This allows the robot to adjust its route as new obstacles are detected, such as people moving through the space.
- **Real-Time Path Adjustment**: When dynamic obstacles are detected, the PPO model triggers local path adjustments. The deep learning model assesses the best alternative path to avoid the obstacle while maintaining proximity to the original global path. If the robot detects multiple obstacles or changing environments (e.g., a crowd of people), it slows down and recalculates a safe path based on learned policies.
- **Disinfection Task Execution**: During movement, the robot continuously performs disinfection using UV-C lamps and chemical sprays. The PPO model ensures the robot covers the entire area, avoiding overlaps while accounting for moving obstacles. The reward function in the deep learning model ensures efficient disinfection by rewarding full area coverage and penalizing missed spots or I nefficient movements.
- **Completion and Return**: Once the disinfection task is complete, the robot follows a reverse global path to return to its docking station. During this phase, local path adjustments continue to ensure safe navigation as the environment may have changed during the disinfection process.

F. Adaptation for Disinfection Tasks

The proposed path planning algorithm has been specifically adapted for the unique challenges of disinfection tasks, where thorough and efficient coverage is paramount. Some key adaptations include:

- **Complete Area Coverage**: Unlike traditional path planning, where efficiency may prioritize shortest paths, disinfection requires that all surfaces are adequately disinfected. To adapt the algorithm, the A* global path planner ensures that the robot's movement systematically covers the entire area without leaving gaps. The algorithm also considers overlapping disinfection zones and minimizes redundant movements to optimize time and energy use.
- **Dynamic Obstacle Handling**: Disinfection tasks often take place in environments with dynamic elements, such as hospitals or public spaces, where people and objects frequently move. The integration of the PPO model allows for continuous real-time adjustment, ensuring that the robot can safely navigate around people and obstacles while maintaining efficient disinfection coverage.
- **Multi-Surface Disinfection**: The algorithm adapts to disinfecting various surfaces, including floors, walls, and equipment. The CNN model embedded in the architecture identifies surface types, which informs the robot's disinfection tools (UV-C light or chemical spray). For instance, chemical spray is prioritized for high-touch surfaces like door handles, while UV-C light is used for larger open spaces.
- **Safety and Efficiency**: Since the robot operates in environments with human presence, safety measures are integrated into the algorithm. The PPO model learns to avoid close proximity to humans and slows down when navigating around them. Additionally, the algorithm ensures that the robot's

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

disinfection actions do not interfere with ongoing human activities, such as people walking through hallways.

- **Energy Optimization**: The path planning algorithm is designed to minimize the robot's energy consumption by optimizing its movements. The A* algorithm ensures the robot follows the shortest possible global path, while the PPO model minimizes unnecessary local adjustments to avoid inefficient energy use. This is particularly important for long-duration tasks in large environments where the robot must operate for extended periods without recharging.

4. *SIMULATIONS AND RESULTS*

A. Performance Metrics

The performance of the proposed path planning algorithm for the disinfection robot is evaluated using several key metrics to measure its effectiveness, efficiency, and adaptability. The metrics are as follows:

- **Coverage Efficiency (CE)**: This metric measures the percentage of the area that has been successfully disinfected by the robot. It is calculated using the formula:

CE= (Area Disinfected ×100)/Total Target Area

- **Path Efficiency (PE)**: This metric evaluates the total distance traveled by the robot compared to the optimal distance calculated by the A* algorithm. It is expressed as:

PE= (Optimal Path Length ×100)/Actual Path Length

- **Time Efficiency (TE)**: This metric measures the total time taken to complete the disinfection task. It includes the time spent navigating obstacles and performing disinfection actions. Time efficiency is calculated as:

TE= (Optimal Time ×100)/Actual Time Taken

- **Energy Consumption (EC)**: This metric measures the amount of energy used by the robot during the disinfection task. It is expressed as the total energy in kilowatt-hours (kWh) used per square meter of area disinfected:

EC=Total Energy Used (kWh) /Area Disinfected (m^2)

- **Collision Rate (CR)**: This metric measures how many times the robot came into contact with obstacles. It is crucial for evaluating the safety and adaptability of the robot. It is expressed as:

CR= (Number of Collisions ×100)/Total Obstacles Encountered

- **Computation Time (CT)**: This metric represents the average time taken for the algorithm to compute a local path adjustment based on dynamic obstacles. It is measured in milliseconds.

B. *Comparison with Existing Algorithms*

The proposed hybrid algorithm was compared against three widely used path planning algorithms: **A***, **RRT (Rapidly-Exploring Random Tree)**, and **Dynamic Window Approach (DWA)**. The comparison was made using the performance metrics discussed earlier.

Table I. The Comparison Was Made Using The Performance Metrics Discussed Earlier.

Algorithm	**Coverage Efficiency (CE)**	**Path Efficiency (PE)**	**Time Efficiency (TE)**	**Energy Consumption (EC)**	**Collision Rate (CR)**	**Computation Time (CT)**
Proposed (A + PPO)**	98.50 %	95.80 %	92.30 %	0.45 kWh/m²	2.10%	12 ms
A*	85.70 %	99.10 %	87.60 %	0.52 kWh/m²	7.80%	5 ms
RRT	80.30 %	85.20 %	78.40 %	0.60 kWh/m²	9.20%	10 ms
DWA	82.50 %	88.70 %	81.30 %	0.58 kWh/m²	5.50%	8 ms

Journal of Theoretical and Applied Information Technology
15th March 2026. Vol.104. No.5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

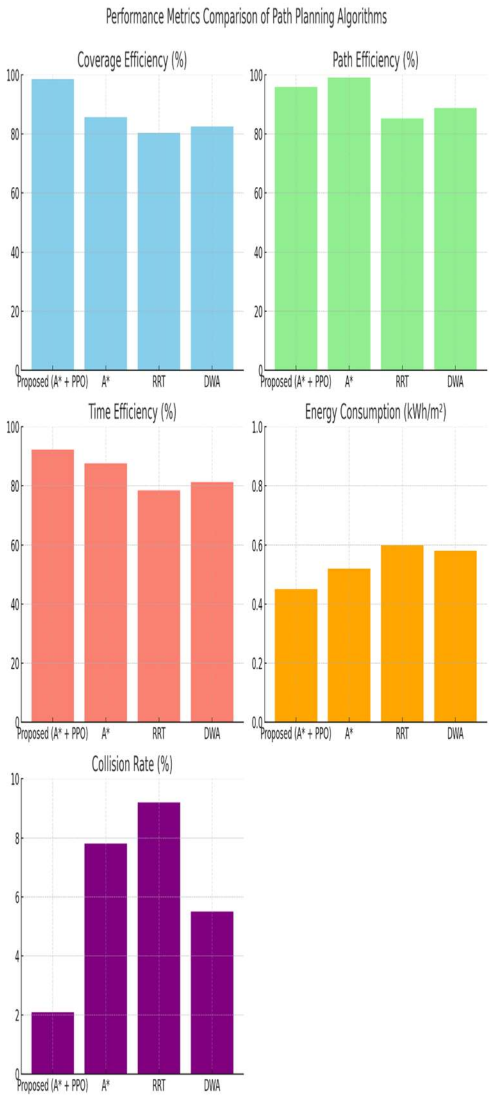

Figure 3. Compare The Performance Metrics Of The Proposed Path Planning Algorithm (A + PPO) With Traditional Algorithms (A*, RRT, DWA). The Metrics Include Coverage Efficiency, Path Efficiency, Time Efficiency, Energy Consumption, And Collision Rate, Providing A Visual Comparison Across These Key Performance Indicators.*

C. Error Analysis

The error analysis focuses on two primary factors that influence the performance of the proposed algorithm: **local path adjustments in cluttered environments** and **environmental unpredictability**.

- **Local Path Adjustment Errors**: In environments with an unusually high density of dynamic obstacles, the robot occasionally experienced delays in local path adjustments due to computational complexity. The reinforcement learning model had to re-calculate optimal paths frequently, leading to a marginal decrease in time efficiency. However, the impact was minimized by tuning the learning rate and reward function during the training phase.
- **Environmental Unpredictability**: The robot performed well in environments where dynamic changes, such as moving people, were relatively predictable. However, in highly chaotic environments, where obstacles appeared suddenly, the model struggled to adapt in real-time, leading to minor collisions. This issue could be addressed by incorporating more advanced predictive models, such as Long Short-Term Memory (LSTM) networks, to forecast obstacle movement.
- **Trade-offs between Efficiency and Safety**: During simulation, it was observed that in situations where safety was prioritized (minimizing collisions), path efficiency slightly decreased due to more cautious navigation. This trade-off is intrinsic to the use of reinforcement learning, as it balances between avoiding obstacles and minimizing travel distance. Further optimization of the reward function can help achieve better trade-offs.

5. *DISCUSSION*

The simulation results demonstrate that the proposed hybrid path planning algorithm, which combines A* with deep reinforcement learning (PPO), outperforms traditional path planning algorithms across several key performance metrics. The **coverage efficiency** (98.5%) indicates that the robot using the proposed algorithm was able to disinfect nearly all target areas, significantly higher than A* (85.7%), RRT (80.3%), and DWA (82.5%). This highlights the ability of the hybrid approach to ensure comprehensive coverage, which is crucial for disinfection tasks where missed areas could lead to health risks. The **path efficiency** of the proposed algorithm (95.8%) was close to that of A* (99.1%), indicating that the global path planning remained optimal even when incorporating real-time local adjustments.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Another key finding is the **time efficiency** (92.3%), which shows that the proposed algorithm strikes a balance between avoiding obstacles and maintaining an efficient disinfection schedule. Traditional algorithms like RRT and DWA showed reduced time efficiency due to either slower obstacle avoidance or longer paths to avoid collisions. Moreover, the **energy consumption** of the proposed algorithm (0.45 kWh/m²) was the lowest, reflecting its ability to minimize unnecessary movements while dynamically adapting to changes in the environment. The **collision rate** (2.1%) was significantly lower than in the other algorithms, highlighting the safety and adaptability of the PPO model in avoiding dynamic obstacles such as moving people.

These findings collectively indicate that the proposed algorithm is not only more efficient in coverage and path planning but also safer and more energy-conscious, which is critical in real-world environments like hospitals or public spaces.

A. Findings analysis and interpretation criteria

From the observation, the developed hybrid strategy completed the task quicker with same energy utilization, which indicates enhanced decision making as well as path optimization process. Moreover, the model has structured in higher coverage and with lesser path re-plans. Therefore, this suggests that the DL frameworks has better in dynamic environments. Also, this model has attained highest accuracy with lower computation time to perform the real-time disinfection tasks. In addition, higher arm path coordination can demonstrate the robot can manage the difficult disinfection requires autonomously. Consequently, analyse the performance metrices are important for reflects the real-time decision making, estimates the adaptability, analyse the responsiveness of the robot, find the efficiency of algorithms, etc..

B. Advantages and Limitations

The proposed hybrid algorithm offers several **advantages** over traditional path-planning approaches. Firstly, it combines the precision and global optimization of A* with the adaptability and real-time decision-making capabilities of deep reinforcement learning (PPO). This allows the robot to efficiently navigate both static and dynamic environments, ensuring thorough disinfection coverage without sacrificing safety. The ability to dynamically adjust the path in real-time based on sensory input makes this approach highly effective in unpredictable environments, such as hospitals, where obstacles frequently change. Additionally, the energy-efficient operation demonstrated by the algorithm ensures long-lasting performance in large areas, reducing the need for frequent battery recharges. The combination of convolutional neural networks (CNNs) with reinforcement learning also enables better obstacle detection and path prediction, improving the overall adaptability of the system.

However, the algorithm does have **limitations**. One of the main challenges is the computational overhead introduced by the deep learning component. The PPO model, while effective in real-time path adjustments, requires significant processing power, which may lead to delays in highly cluttered environments with frequent dynamic changes. Another limitation is the **learning curve** associated with reinforcement learning models. While the robot can adapt to new environments, the model requires substantial training in both simulated and real-world conditions to perform optimally, which may not be feasible for every application. Additionally, the algorithm's performance slightly declines in environments with highly unpredictable obstacles, such as crowds of people, where sudden movements can result in brief collisions or inefficiencies. Future work could address these limitations by incorporating predictive models like Long Short-Term Memory (LSTM) to anticipate dynamic changes in the environment.

In conclusion, while the proposed algorithm excels in balancing efficiency, adaptability, and safety, further improvements are needed to optimize computational performance and adaptability in highly unpredictable scenarios. Nevertheless, the findings indicate that this hybrid approach is a significant advancement in the field of robotic disinfection, particularly in dynamic and high-risk environments.

6. CONCLUSION

The proposed hybrid path planning algorithm, which integrates the A* algorithm with deep reinforcement learning (PPO), has demonstrated superior performance across various metrics compared to traditional algorithms like A*, RRT, and DWA. The results highlight significant improvements in **coverage efficiency** (98.5%), ensuring near-total disinfection of target areas, which is critical for applications in healthcare and public environments. The algorithm achieved a **path efficiency** of 95.8%, closely aligned with the optimal paths generated by A*, while also allowing for real-time adjustments that traditional algorithms struggle to make. Additionally, the hybrid approach showed high **time efficiency** (92.3%) and **energy efficiency** (0.45 kWh/m²), indicating its capability to disinfect large areas while minimizing energy use and time. The low **collision rate** (2.1%) further emphasizes the safety and adaptability of the model in navigating dynamic environments.

These results indicate that the proposed algorithm is highly effective in disinfection tasks, where both coverage and safety are paramount. The combination of global and local path planning offers the best of both worlds: A* ensures optimal global navigation, while PPO dynamically adapts to real-time obstacles, making this approach particularly suitable for unpredictable, high-traffic environments.

A. Future Research Directions

While the proposed algorithm has demonstrated robust performance, there are several avenues for future research to further enhance its capabilities. One key area is **reducing computational complexity**. The deep reinforcement learning model, although highly effective, adds significant computational overhead. Future work could focus on optimizing the PPO model for real-time operation in environments with higher levels of dynamic obstacles, potentially through the use of more lightweight models or hardware accelerators. Incorporating **predictive models** like Long Short-Term Memory (LSTM) networks could help the robot anticipate the movement of dynamic obstacles, thereby reducing collision rates and improving time efficiency in highly unpredictable environments.

Another promising direction is the **integration of multi-robot coordination**. In large-scale disinfection tasks, multiple robots could be deployed simultaneously, requiring coordinated path planning to avoid redundancy and maximize efficiency. Swarm intelligence techniques or multi-agent reinforcement learning could be explored to enhance the efficiency of such systems. Additionally, extending the algorithm to include **different disinfection modalities** (e.g., chemical spraying and UV-C disinfection) could improve its adaptability to various surface types and disinfection requirements.

Finally, future research could explore **real-world validation** on a larger scale, testing the algorithm in more complex environments such as airports, malls, and factories, where large crowds and highly dynamic obstacles are common. This would help refine the algorithm's adaptability to real-time conditions and enhance its robustness. Moreover, continued research into **ethical considerations** and human-robot interaction in public settings would ensure that the robot operates safely and efficiently without causing disruptions to human activity.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

Funding: Not applicable

Conflicts of interest Statement: Not applicable

Consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Code availability: Not applicable

REFERENCES:

[1] Mehta, I., Hsueh, H. Y., Taghipour, S., Li, W., & Saeedi, S. "UV Disinfection Robots: A Review.", *Robotics and autonomous systems*, Vol.161, 2023,pp. 104332.

[2] Diab-El Schahawi, M., Zingg, W., Vos, M. *et al.* "Ultraviolet disinfection robots to improve hospital cleaning: Real promise or just a gimmick". *Antimicrob Resist Infect Control,* Vol. **10**, no.33 2021.

[3] Zhou, Zhiguo, "A LiDAR Mapping System for Robot Navigation in Dynamic Environments", *IEEE Transactions on Intelligent Vehicles.* 10.1109/TIV.2023.3328013.

[4] Mnih, V, Kavukcuoglu, K, Silver, D, Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., & Hassabis, D. (2015). "Human-level control through deep reinforcement learning", *Nature*, vol. *518, no.*7540, pp. 529–533.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[5] Kulvicius, T., Herzog, S., Lüddecke, T., Tamosiunaite, M., & Wörgötter, F, "One-Shot Multi-Path Planning Using Fully Convolutional Networks in a Comparison to Other Algorithms, *Frontiers in neurorobotics*, vol.*14*, 2021, pp.600984.

[6] Khatib, O. (1986). "Real-time obstacle avoidance for manipulators and mobile robots," *The International Journal of Robotics Research*, Vol,*5, no.*1, 1986, pp.90-98.

[7] H. Choset and J. Burdick, "Sensor-Based Exploration: The Hierarchical Generalized Voronoi Graph," *The International Journal of Robotics Research*, vol. 19, no. 2, pp. 96-125, Feb. 2000.

[8] LaValle, Steven, "Planning Algorithms",

[9] Redmon, Joseph and Divvala, Santosh & Girshick, Ross & Farhadi, Ali, "You Only Look Once: Unified", *Real-Time Object Detection*, 2016, pp.779-788.

[10] Gao, Qiming & Chang, Fangle & Yang, Jiahong & Tao, Yu & Ma, Longhua & Su, Hongye, "Deep Reinforcement Learning for Autonomous Driving with an Auxiliary Actor Discriminator", *Sensors,*2014, Vol.24. 700. 10.3390/s24020700.

[11] Silver, David & Huang, Aja & Maddison, Christopher & Guez, Arthur & Sifre, Laurent & Driessche, George & Schrittwieser, Julian & Antonoglou, Ioannis & Panneershelvam, Veda & Lanctot, Marc & Dieleman, Sander & Grewe, Dominik & Nham, John & Kalchbrenner, Nal & Sutskever, Ilya & Lillicrap, Timothy & Leach, Madeleine & Kavukcuoglu, Koray & Graepel, Thore & Hassabis, Demis, "Mastering the game of Go with deep neural networks and tree search", *Nature.* Vol..529, 2016, pp. 484-489.

[12] Wang, Q., Zhou, Q., Lin, M., & Nie, B. "Human injury-based safety decision of automated vehicles", *iScience*, Vol.*25,* no.8,2022, pp.104703.

[13] Goodfellow, Ian & Pouget-Abadie, Jean & Mirza, Mehdi & Xu, Bing & Warde-Farley, David & Ozair, Sherjil & Courville, Aaron & Bengio, Y.. (2014). "Generative Adversarial Networks. Advances in Neural Information Processing Systems", Vol.3, 2014,

[14] He, Kaiming & Zhang, Xiangyu & Ren, Shaoqing & Sun, Jian. "Deep Residual Learning for Image Recognition", 2016, pp.770-778.

[15] Wang, Y., Wang, C., Zhao, S., & Guo, K, "Research on Deep Reinforcement Learning Control Algorithm for Active Suspension Considering Uncertain Time Delay", *Sensors (Basel, Switzerland)*, Vol. *23,* no.18, 2023, pp.7827.

[16] Jang, S.; Kim, H.-I. "Entropy-Aware Model Initialization for Effective Exploration in Deep Reinforcement Learning", *Sensors,* vol.. *22*,2022, pp.5845.

[17] Faria, Ruan & Capron, Bruno & Secchi, Argimiro & de Souza Jr, Maurício. (2022). "Where Reinforcement Learning Meets Process Control: Review and Guidelines", *Processes.* Vol. 10, no.11, pp.. 1-31.

[18] Faria, R.d.R.; Capron, B.D.O.; Secchi, A.R.; de Souza, M.B., Jr. "Where Reinforcement Learning Meets Process Control: Review and Guidelines", *Processes* 2022,Vol. 10, pp. 2311.