Dynamic Path Planning for Autonomous Robots in Forest Fire Scenarios Using Hybrid Deep Reinforcement Learning and Particle Swarm Optimization

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Abstract*—The growing frequency of forest area fires poses critical challenges for emergency response, necessitating progressive solutions for effective navigation and direction planning in dynamic environments. This study investigates an adaptive technique to enhance the performance of autonomous robots deployed in forest area fireplace scenarios. The primary objective is to develop a hybrid methodology that integrates advanced studying strategies with optimization techniques to enhance route planning beneath unexpectedly changing situations. To reap this, a simulation-based total framework became hooked up, in which self-reliant robots were tasked with navigating diverse forest fire eventualities. The method includes schooling a model to dynamically adapt to environmental modifications at the same time as optimizing direction choice in real time. Performance metrics together with direction efficiency, adaptability to obstacles, and reaction time been analyzed to assess the effectiveness of the proposed solution. Results indicate an enormous improvement in path planning performance as compared to traditional methods, with more suitable adaptability main to faster response instances and extra effective navigation. The findings underscore the functionality of the proposed method to cope with the complexities of forest area fire environments, demonstrating its potential for real-world applications in disaster response. The results are shown in the conceived DRL-PSO framework where execution time is reduced up to 95% and the success rate of 95 % for the proposed method compared to the conventional ones. Python is used to implement the proposed work. Compared to the proposed method's execution time of 68. 3 seconds and the highest success rate among evaluated strategies, so it can be used as a powerful solution for autonomous drone navigation in dangerous situations. In the end, this research contributes precious insights into adaptive route planning for self-sufficient robots in unsafe situations, providing a strong framework for destiny advancements in disaster management technologies.

***Keywords*—Adaptive path planning; deep reinforcement learning; disaster environments; drone rescuing; particle swarm optimization; forest fire**

I. Introduction

As a result of climate change and human activity, forest fires have become more severe and frequent threats posing serious threats to human safety and ecosystems These flames spread rapidly, and their unpredictable nature necessitates using state-of-the-art technological solutions for efficient monitoring and rescue efforts RL) using those tasked with rescuing people in active forest fire situations The platform offers a new approach develop a flexible system for drones by using fire detection information and real-time data to inform and optimize the autonomous drone approach planning processes [1]. Drones can operate safely and effectively in a dangerous environment thanks to fire detection data, which provides vital information about fire locations and severity spread. Path planning is important in robotics, with the aim of determining the optimal path of material movement from start to finish, which can be used in aerospace, military, manufacturing, agriculture. A subset of autonomous guidance requires dynamic decisions as a robot moves forward toward its goal. Recent advances in participatory navigation and UAV technologies highlight their high scalability, scalability and adaptability for various applications such as search and rescue [2], agriculture, and inspection. UAVs are designed to operate without human intervention, making them ideal for projects such as visual inspection of large buildings. An important approach in this area is Coverage Path Planning (CPP), which focuses on efficient, collision-free paths that cover all important paths in an area Path planning can be offline, online, or hybrid, in which online channels are important for dynamic, unfamiliar environments and where robots must continuously collect and process distance data to safely navigate Challenges such as optimal, collision avoidance Method a three-dimensional planning is adopted in UAVs often using global solutions for complex problems and local solutions for dynamic constraints visibility graphs, fast searching random trees, probabilistic routing, . algorithms There are, although reasoning methods do not always find the best methods [3].

Intelligent transportation systems (ITS) [4] are aimed at increasing road capacity, reducing accidents, improving efficiency and reducing congestion, as well as reducing energy consumption and environmental impact Vehicles as it automatically develop key components of the ITS, including environmental concepts, road design, tracking and monitoring. The key to participatory transportation planning is to identify efficient, collision-free routes from the starting point to the destination [5]. Various path-planning algorithms have emerged, including geometric, graph search, intelligent bionic, artificial potential field, and sampling-based algorithms like RRT and probabilistic roadmap, which excel in complex environments. Traditional RRT methods focus on finding paths but lack efficiency in convergence, search speed, and path optimality. Improvements like Biased RRT, Bi-RRT, RRT-connect, and RRT address these issues but often neglect vehicle-specific constraints. For dynamic environments, algorithms like potential field combinations and enhanced Bi-RRT adapt paths in real-time, accounting for dynamic obstacles. Recent advancements integrate reinforcement learning and heuristic methods to enhance RRT-based planning for smooth, collision-free paths in complex scenarios [6]. Path optimization techniques such as cubic B-splines, Dubins curves, and path pruning further refine paths, though challenges remain in maintaining curvature consistency and minimizing control difficulty. Disaster events like fires, floods, and landslides demand urgent and efficient rescue measures to minimize economic losses and threats to human life. Drones have become essential in disaster rescue, offering advantages such as 3D map reconstruction, emergency mapping, and environmental assessment. Multi-drone systems are particularly useful in complex terrains where traditional rescue methods struggle. However, effective mission planning for drones involves addressing environmental challenges and drone performance constraints. Heuristic algorithms like genetic algorithms (GA) and particle swarm optimization (PSO) are commonly used for mission planning but face issues like slow convergence and local optima. To overcome these limitations, this paper proposes improved GA and PSO algorithms for mission planning in complex 3D environments [7].

Autonomous vehicle systems, especially mobile robots, and autonomous vehicles have received considerable attention and commercialization, especially in the field of logistics and services in the service industry. The widespread use of reinforcement learning is limited by long training periods and limited computational resources Despite the advantages of DRL, such as intensive learning and large sensor dependence reduced, training in challenging environments is time-consuming and can lead to poor performance due to localized practice played a role. The high-quality research on DRL-based active obstacle avoidance and road systems from 2018 to 2022, identifying gaps and proposing future research directions to improve safety , efforts, and potential growth in this field [8]. Existing systems for route planning in autonomous robotic and mobile systems exhibit several shortcomings. Traditional RRT methods work well for challenging terrain but perform poorly in speed matching and road optimization, with enhanced versions such as Bi-RRT and RRT-Connect often ignoring vehicles specifically limited. They struggle with slow convergence and local change. Heuristic algorithms such as GA and PSO also face problems of slow convergence and local adaptability, especially in complex 3D environments. DRL methods, although powerful, have long training times and high computational resource requirements and result in poor performance due to localized action execution AMRs, although simpler than AGVs, need to be limited by movement in for safety, and limits their operating range. The proposed DRL model addresses these issues by using real-time data for informed decision-making, integrating DRL into advanced road planning processes to increase efficiency and safety, and DRL and integrating PSO to improve robustness and performance This approach ensures flexibility and resilience scenarios are appropriate, and achieves high accuracy and reliability through the traditional DRLC limitations of training time and estimation by the effortful handling.

The major key contribution are as follows:

- The study introduces a novel hybrid approach combining Deep Reinforcement Learning (DRL) with Particle Swarm Optimization (PSO), enhancing the efficiency and adaptability of independent robots in navigating complicated, dynamic catastrophe environments.
- The proposed approach permits real-time adaptation to unexpectedly changing environmental situations and obstacles normally determined in disaster zones, improving the robots' capacity to make well timed and optimal decisions
- The research contributes to multi-agent structures through demonstrating how multiple independent robots can collaborate successfully to gain common desires, which includes search-and-rescue operations, by leveraging DRL and PSO coordination abilities
- The model optimizes computational aid utilization through the integration of DRL and PSO, permitting robots to carry out path-making plans with decreased computational overhead while retaining high-performance stages.

The research validates the model by using the simulations in practical dynamic disaster environments, showing extensive enhancements in pathfinding efficiency, robustness, and undertaking of entirety in comparison to traditional techniques.

The proposed research is arranged as follows: The current models are reviewed in Section II. In Section III, the drawbacks of the existing frameworks are briefly reviewed. In Section IV, the proposed approach and methodology are addressed in detail. Section V discusses the result and finally, Section VI presents the conclusions of this study.

II. Related Work

Yao et al., [9] address the complex mobility constraints faced by autonomous robots operating in greenhouse environments. Their research highlights the need for accurate mapping, precise localization, and robust road planning specifically tailored to the challenges of agricultural conditions. A key aspect of their approach is the development of a centralized hardware system that integrates multiple sensors. This integration aims to effectively reduce the environmental impact that occurs in a greenhouse environment, thus increasing the reliability of the entire system. The concept of their innovations is to deal with modules for restoration role in the LeGO-LOAM system. These modules play an important role in improving the accuracy of pose estimation by significantly reducing the absolute pose error (APE) to 24.42%, as shown in their experiments Furthermore, their Enhanced OpenPlanner features sophisticated algorithms that it covers important factors in the cost of agricultural products A hysteresis strategy has been introduced to ensure stable variation, and contributes to improved operational efficiency. Although the findings show promise in greenhouse applications, many challenges remain. Scaling up their solutions to larger farms poses a significant barrier. However, this study faces challenges such as handling dynamically changing greenhouse environments, limited real-world testing, and dependency on structured infrastructure. Localization remains problematic due to unreliable GPS in indoor settings, and the system's computational demands may restrict deployment on low-cost robotic platforms, limiting overall flexibility and scalability. Addressing these challenges will be crucial for their proposed system to be widely adopted and effective under agricultural conditions.

Kiani et al. [10] delve into the complex demanding situations of direction-making plans and dynamic impediment avoidance for Unmanned Surface Vehicles (USVs) running within maritime environments. Their studies introduce a revolutionary vehicle-obstacle avoidance methodology employing the Ant Colony Algorithm (ACA) and Clustering Algorithm (CA). This method dynamically adjusts seek parameters to optimize direction planning performance via adapting to the complexities of the surroundings. A key characteristic of their approach is the law and smoothing of the dynamic search path, which efficaciously minimizes route period and turning angles, as evidenced by their simulation outcomes throughout diverse impediment distributions. Despite demonstrating successful direction planning abilities, the sensible implementation of their technique faces sizeable computational challenges, especially in situations with congested maritime traffic. The real-time decision-making needs in such dynamic and complicated environments present barriers to the seamless integration and operational effectiveness in their proposed technique. Overcoming those computational hurdles could be essential for boosting the feasibility and reliability in their approach in real-international maritime programs.

In their comprehensive 2019 study Liu et al., [11] explore the intricacies of 3-d course planning for mobile robots in particular designed for agricultural environments. Their research specializes in the software of metaheuristic algorithms, inclusive of Incremental Gray Wolf Optimization (I-GWO) and Expanded Gray Wolf Optimization (Ex-GWO), geared toward correctly guiding robots via large and densely populated farmlands. The number one objective in their technique is dual-fold: first, to optimize route planning via minimizing computational overhead and aid utilization; 2d, to make certain sturdy obstacle avoidance talents. Through rigorous simulations, Liu et al., Exhibit promising outcomes, highlighting the Ex-GWO algorithm's outstanding fulfillment with a 55. 56% fulfillment in optimizing path prices. Despite those improvements, big demanding situations stay. Adapting those algorithms to diverse agricultural terrains poses hurdles, as does ensuring well timed responsiveness to dynamic limitations encountered in practical area operations. Addressing those challenges is vital to decorate the versatility and reliability in their technique for real-global agricultural packages, in the end paving the manner for greater green and effective robotic operations in complex agricultural landscapes.

In their latest suggestion, Wu and Low [12] the Adaptive Path Replanning (APReP) technique designed specifically for drones navigating thru dynamic city environments. Their technique innovatively categorizes various sorts of dynamic environmental adjustments and develops tailor-made strategies for green path replanning, suitable for each single and multi-drone missions. Central to their technique is the discrete rapidly exploring random tree algorithm, meticulously designed to generate paths that align with the discrete traits of city landscapes. Extensive validation through simulations underscores the effectiveness of their techniques in addressing the problematic challenges posed by way of large-scale city dynamics. Their method demonstrates strong overall performance in managing more than one dynamic changes, thereby improving adaptability and operational reliability in complex city situations. However, essential challenges continue to be, consisting of the need to improve coordination amongst more than one drones and ensure real-time responsiveness to sudden environmental fluctuations. These regions call for similarly refinement to decorate the general efficiency and applicability of the APReP approach for optimizing drone operations in dynamic city settings.

Chang et al., [13] propose to further enhance the dynamic window method (DWA) for path planning of mobile robots in unknown environments, using Q-learning and their study focuses on the analytical application of DWA preparing and carefully defining conditions and work environments towards enabling global logistics operations. By integrating Q-learning, their approach facilitates adaptive changes at scale in response to real-time environmental feedback, increasing efficiency and success rate high in complex unfamiliar processes Limitations such as the need for adequate training data to ensure and ongoing learning processes. Addressing these challenges is essential to improve the reliability and applicability of their enhanced DWA methods in real-world scenarios, and paves the way for more efficient and adaptable transportation systems in different environments. However, the implementation faces hurdles such as the requirement for substantial training data and ongoing learning processes to ensure sustained adaptation to evolving environmental dynamics in practical applications. Addressing these challenges is crucial to furthering the reliability and applicability of their enhanced DWA approach in real-world scenarios, paving the way for more effective and adaptive autonomous navigation systems in diverse and dynamic environments.

Zhuang et al., [14] presented a sophisticated design of collaborative routing systems for autonomous underwater vehicles (AUVs) operating in dynamic environments Their approach is with global methods such as Legendre pseudo spectral the use of access to efficiently plan inconsistent paths in steady state It is designed to connect the points, which provided secure access between the control nodes A key feature of their design is real-time integration of design strategies, including local restructuring strategies that take advantage of the differential flatness property of AUVs this provides rapid response to unexpected dynamic obstacles encountered during missions on. While their system proves effective in avoiding collisions in dynamic underwater conditions, challenges continue in scaling up to accommodate larger AUV crews and adapting them to withstand changes real-time in the environment with ease. While their framework proves effective in managing collision avoidance in dynamic underwater scenarios, challenges persist in scaling the approach to accommodate larger teams of AUVs and in enhancing its adaptability to cope seamlessly with real-time changes in environmental conditions. Addressing these challenges is crucial for advancing the practical deployment and operational efficiency of cooperative AUV missions in complex and evolving underwater environments.

Azizi et al., [15] introduces a new heuristic fire-hawk optimization algorithm that is called the FHO founded on consideration of; the feeding ecology of Whistling kites, Black kites and Brown falcons. These birds are termed Fire Hawks, special regarding the specific gestures they make to capture prey in nature, especially through the mechanism of setting free. It falls into conflict for the simple reason that nature, especially through the mechanism of setting free, Applying the described algorithm, a numerical It was conducted an investigation on 233 mathematical test functions ranging from 2 to 100 dimensions and total of 150 000 function evaluations were used for optimization. In contrast, there are alternative approaches where ten different classical and new metaheuristic algorithms were employed. The statistical aspects include the max, average, median, and deviation of 100 independent optimization runs Other statistical tests that were used were the Kolmogorov–Smirnov test, Wilcoxon test, Mann–Whitney test, Kruskal–Walli's test, and the Post Hoc test. The results obtained in the experiments confirm the superiority of the FHO algorithm compared to the other algorithms described in the literature. Moreover, two of the most recent CECs that are the bound constraint problems CEC 2020 and the real-world optimization problems including the mechanical engineering design problems CEC 2020 were considered for evaluating the performance of the FHO algorithm, which again clearly showed the enhanced performance of the optimizer over the other metaheuristic algorithms in literature. The performance of the FHO is also measured when solve the two actual size structural frames of 15 and 24 stories where the new method is better than the previously developed metaheuristics.

Obayya et al., [16] introduce an study devises an Improved Bat Algorithm with Deep Learning Based Biomedical ECG Signal Classification (IBADL-BECGC) approach. To accomplish this, the proposed IBADL-BECGC model initially pre-processes the input signals. Besides, IBADL-BECGC model applies NasNet model to derive the features from test ECG signals. In addition, Improved Bat Algorithm (IBA) is employed to optimally fine-tune the hyperparameters related to NasNet approach. Finally, Extreme Learning Machine (ELM) classification algorithm is executed to perform ECG classification method. The presented IBADL-BECGC model was experimentally validated utilizing benchmark dataset. The comparison study outcomes established the improved performance of IBADL-BECGC model over other existing methodologies since the former achieved a maximum accuracy of 97.49%.

In recent years, many metaheuristic algorithms have attempted to explore feature selection, such as the dragonfly algorithm (DA). Dragonfly algorithms have a powerful search capability that achieves good results, but there are still some shortcomings, specifically that the algorithm's ability to explore will be weakened in the late phase, the diversity of the populations is not sufficient, and the convergence speed is slow. To overcome these shortcomings, Chen et al., [17] propose an improved dragonfly algorithm combined with a directed differential operator, called BDA-DDO. First, to enhance the exploration capability of DA in the later stages, we present an adaptive step-updating mechanism where the dragonfly step size decreases with iteration. Second, to speed up the convergence of the DA algorithm, we designed a new differential operator. We constructed a directed differential operator that can provide a promising direction for the search and then sped up the convergence. Third, we also designed an adaptive paradigm to update the directed differential operator to improve the diversity of the populations. The proposed method was tested on 14 mainstream public UCI datasets. The experimental results were compared with seven representative feature selection methods, including the DA variant algorithms, and the results show that the proposed algorithm outperformed the other representative and state-of-the-art DA variant algorithms in terms of both convergence speed and solution quality.

This literature review examines various optimization algorithms for self-sufficient systems in dynamic environments, highlighting their strengths and drawbacks. Yao et al. deal with mobility constraints in greenhouses however conflict with GPS reliability and scalability. Kiani et al. consciousness on impediment avoidance for Unmanned Surface Vehicles, going through computational challenges in congested maritime settings. Liu et al. optimize

3D path planning for agriculture but come across adaptability troubles in diverse terrains. Wu and Low broaden an Adaptive Path Replanning technique for drones however need to decorate multi-drone coordination. Chang et al. enhance the dynamic window approach for cell robots but require widespread training data. Zhuang et al. and Azizi et al. present collaborative systems and fire-hawk algorithms, respectively, facing scalability and comparative overall performance challenges.

III. Problem Statement

The current methods of autonomous navigation in dynamic environments including greenhouse, maritime, and urban environments have their shortcoming that affects their efficiency. Most approaches fail at some point to respond quickly and dynamically to time varying conditions that modify continually the environment of execution, which leads to a decrease in the level of the process performance and an increase in the total time required for the process execution [18]. However, there are several disadvantages to some of these approaches, for example, the computational problems as well as the requirement of access to large amounts of training data. The avoidance of the obstacles in the traditional systems may not address well the dynamic and unpredictable scenarios hence higher collision rates and reduced success rates in the real world. Some of the challenges previously avoided include; lack of real time adaptability [19], inefficient routing and poor or non-existent obstacle avoidance which the proposed work that incorporates DRL integrated with PSO will be able to overcome since it offers real time adaptability, improved routing and obstacle avoidance in a dynamic disaster environment.

IV. Integrated Framework for Adaptive Path Planning Using Deep Reinforcement Learning and PSO in Dynamic Forest Fire Environment

In the proposed study, the integrated framework for adaptive path-making plans combines Deep Reinforcement Learning (DRL) and Particle Swarm Optimization (PSO) to navigate an unmanned device via dynamic wooded area fire surroundings. DRL plays a vital role in real-time decision-making, permitting the system to analyses premiere navigation techniques by interacting with the environment. This learning system adapts the gadget to unpredictable changes, which include the spread of the fire or new boundaries. Through DRL, the machine receives comments from the environment, updating its rules for more secure and efficient navigation. PSO enhances DRL by optimizing the decision-making technique in complicated multi-objective situations. Its quality-tunes the navigation route by balancing exploration (searching new paths) and exploitation (utilizing best-recognized paths). PSO is especially effective in continuously adjusting key parameters, like averting fire-prone areas while aiming for a target region. The aggregate of DRL's learning capabilities and PSO's optimization guarantees that the system learns the best techniques but additionally correctly adapts to actual-time adjustments in the surroundings. By integrating these procedures, the framework dynamically adjusts to the evolving nature of forest fires, offering a strong and adaptive solution to complicated navigation challenges, and making sure safe and well-timed response in fire management eventualities.

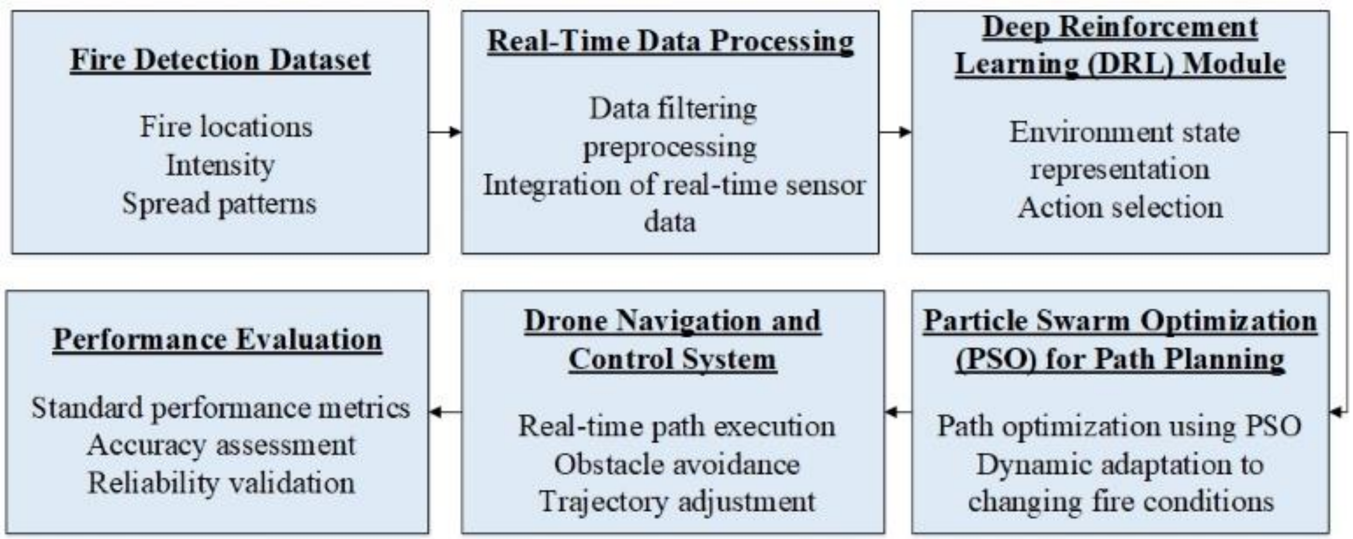

Fig. 1. Integrated system for adaptive path planning of drones in dynamic forest fire environments.

Fig. 1 illustrates the comprehensive fire detection and drone navigation system integrates multiple components for effective emergency management. It processes fire data and real-time sensor inputs, utilizing Deep Reinforcement Learning (DRL) for decision-making and Particle Swarm Optimization (PSO) for dynamic path planning. The drone navigation system adjusts in real-time to avoid obstacles and changes in fire behavior, while performance evaluations ensure reliability and accuracy. Together, these technologies optimize fire detection and enhance response efficiency in dynamic environments.

A. Data Collection

The Fire Detection Dataset [20] available on Kaggle is vital to the proposed framework for adaptive path making plans of autonomous drones in dynamic forest fire environments. This dataset includes attributes along with the date, range, and longitude of hearth incidents, as well as the brightness temperature, scan width, track height, acquisition date and time, satellite and device information, detection confidence, dataset model, brightness temperature at 31 microns, Fire Radiative Power, and whether or not the fireplace changed into detected in the course of the day or night. In the proposed framework, this dataset serves multiple important features. Firstly, it enables specific identification and real-time tracking of hearth places and intensities via consuming and processing facts attributes to pinpoint the exact geographical places and characteristics of fires. The actual-time data processing module integrates those facts points with live sensor inputs from drones, making sure well timed and correct information flows into the gadget. The DRL module then makes use of this information to dynamically understand and adapt to the modern nation of the environment, learning surest navigation techniques to avoid hearth zones. The PSO algorithm similarly refines direction making plans by means of adapting routes in real-time based on fire intensity and spread styles, the usage of metrics like FRP and brightness to modify drone trajectories for secure and efficient navigation. Additionally, the dataset supports the performance assessment of the system, supplying floor truth data for assessing detection accuracy, response instances, and navigation success quotes. Thus, the Fire Detection Dataset is crucial for enabling the framework's sturdy and adaptive path planning competencies.

B. *Data Pre-Processing*

The preprocessing of the Fire Detection Dataset inside the proposed framework is a crucial step to ensure correct and powerful adaptive course planning for autonomous drones in dynamic wooded area fireplace environments. Initially, raw statistics from the dataset undergoes an intensive cleansing method, which incorporates managing lacking values, casting off duplicates, and correcting any inconsistencies. This step guarantees the integrity and reliability of the information. Next, the dataset is filtered to keep most effective the maximum applicable attributes, which includes date, latitude, longitude, brightness temperature, detection and Fire Radiative Power (FRP), which are essential for actual-time fireplace detection and tracking. Following the cleaning and filtering steps, the statistics is normalized to convey all attribute values right into a consistent variety, which aids inside the green processing and correct analysis via the gadget gaining knowledge of algorithms.

The temporal attributes like acquisition date and time are transformed into a standardized layout to facilitate time-series evaluation and monitoring of fireplace development over the years. Geographical coordinates are converted into a format compatible with the drone's navigation gadget, making sure of specific geospatial awareness. The preprocessed statistics is then integrated with real-time sensor information from the drones, merging static historical facts with dynamic, real-time inputs to offer a comprehensive and up-to-date photograph of the fire surroundings. This incorporated dataset feeds into the Deep Reinforcement Learning (DRL) module, which uses it to train and continuously update the navigation model, permitting drones to adapt their paths in response to actual-time hearth dynamics. By meticulously preprocessing the dataset, the framework guarantees that the drones have get right of entry to tremendous.

C. *DRL and PSO Integrated Workflow for Dynamic Disaster Navigation*

The DRL workflow of the proposed framework for adaptive route planning of autonomous drones in dynamic forest fire environment is designed to enable real-time decision making and optimal navigation Performance the process begins with a representation of environmental conditions, where Pre-processed fire detection data are used, with factors such as fire location, severity, spread, etc. are added, to explain the current situation S_t of the environment. This state S_t is a comprehensive snapshot of fire scenario at time t.

The DRL model employs a policy $\pi(a_t|S_t;\theta)$ parameterized by θ, which maps the state S_t to an action a_t, representing the drone's navigational decisions. The action a_t could involve moving to a new location, altering altitude, or performing a specific maneuver to avoid obstacles and optimize the path. The policy is typically modeled using a neural network, which is trained to maximize the expected cumulative reward R_t. The reward function R_t is designed to incentivize desirable behaviors, such as minimizing travel time, avoiding obstacles, and accurately reaching target locations. It can be defined in the Eq. (1)

$$R_t = \sum_{k=t}^{T} \gamma^{k-t} \gamma_k \tag{1}$$

where γ is the discount factor that prioritizes immediate rewards over distant future rewards, and γ_k represents the reward received at time k. The training process involves iteratively updating the policy parameters θ using gradient descent methods. One popular approach is the Q-learning algorithm, where the Q-value ($Q(S_t, a_t; \theta)$ estimates the expected utility of taking action a_t in state S_t as illustrated in the Eq. (2)

$$Q(S_t, a_t; \theta) = r_t + \gamma max_{a'} Q(S_{t+1}, a'; \theta) \tag{2}$$

The drone interacts with the environment, collects experiences (s_t, a_t, r_t, S_{t+1}) and stores them in a replay buffer. The neural network parameters are periodically updated by minimizing the loss function as represented in the Eq. (3)

$$L(\theta)=E[(r_t + \gamma max_{a'} Q(S_{t+1}, a'; \theta^-) - Q(S_{t+1}, a'; \theta))^2] \tag{3}$$

where, θ^- represents the parameters of a target network, which is periodically synchronized with θ. PSO has been integrated to optimize the DRL design by evaluating several possible solutions, which will increase the efficiency and performance of the road system. This hybrid approach ensures that drones can dynamically adapt to changing fire conditions, travel safely, and make decisions in real-time accuracy, ultimately providing rescue operations effective in hazardous areas is effective.

D. *Particle Swarm Optimization (PSO) Workflow for Adaptive Path Planning*

The PSO workflow within the proposed framework for adaptive path planning of autonomous drones in dynamic forest fire environments plays a crucial role in optimizing navigation paths by simulating the social behavior of birds flocking or fish schooling. Each potential solution, called a particle, represents a candidate path for the drone, characterized by a position vector x_i in the solution space and a velocity vector v_i dictating the particle's movement. The position vector x_i denotes the drone's coordinates in the environment, while the velocity vector influences the path direction and speed adjustments.

The workflow begins with initializing a swarm of particles randomly distributed across the solution space. Each particle i has an associated position $x_i(t)$ and velocity $v_i(t)$ at time t, as well as a memory of its best-known position p_i (personal best) and the global best position g discovered by the swarm. The particles' velocities and positions are updated iteratively to explore the solution space and converge towards the optimal path. The velocity update rule combines three key influences: inertia, personal best, and global best, governed by the following Eq. (4).

$$v_i(t+1) = wv_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (g - x_i(t) \tag{4}$$

where w is the inertia weight balancing exploration and exploitation, c_1 and c_2 are cognitive and social acceleration coefficients, respectively, and $r_1 and$ r_2 are random numbers uniformly distributed in [0,1]. The new position of particle (i) is then updated by the Eq. (5).

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{5}$$

In the context of dynamic forest fire environments, particles represent various path trajectories for the drone. The fitness function evaluates each particle's position based on criteria such as distance to the target, obstacle avoidance, and fire intensity. The fitness function $f(x_i)$ can be formulated to minimize a combination of these criteria as shown in the Eq. (6).

$$f(x_i) = \propto d(x_i, target) + \beta \sum_{obstacles} \frac{1}{d(x_i, obstacles)} + \gamma \sum_{fire\ Zones} intensity(x_i) \tag{6}$$

where $\propto$, β and γ are the distance to the target, proximity to obstacles, and intensity of fire are weighting factors. Throughout the iteration process, particles effectively communicate with their individuality and update the global optimal position based on fitness checks. The DRL module readjusts the processes generated by PSO by optimizing production schedule changes and real-time adjustments. By combining PSO and DRL, the system uses the global search capability of PSO to find optimal path solutions and the learning capability of DRL to dynamically optimize and solve these paths in real time. This approach it is this synergy ensures safe and effective navigation for autonomous drones, unexpected and dangerous forest fires. It enhances their ability to conduct effective pursuit and rescue operations under different circumstances.

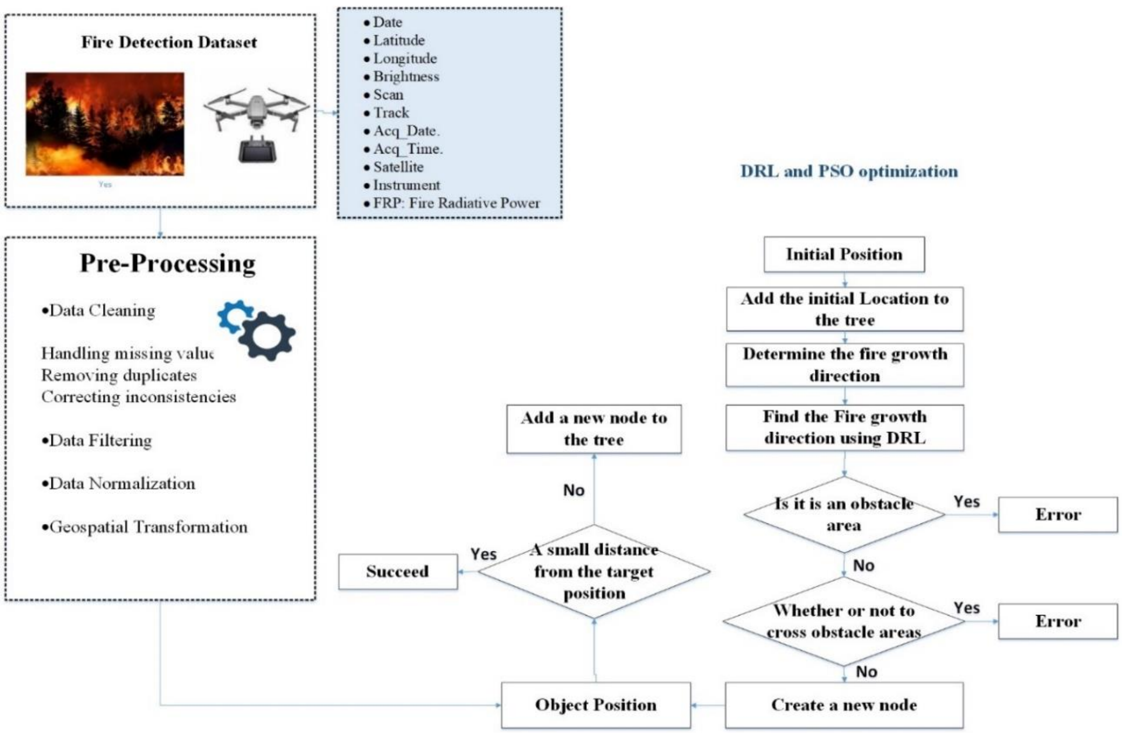

Fig. 2. Framework for adaptive path planning of autonomous drones in dynamic forest fire environments.

Fig. 2 shows a detailed schematic of adaptive strategies for autonomous drones in active forest fires. This form line is part of the dawn, and the in-depth reinforcing education is combined with an unhindered hybrid mindset, the form line begins with the fire detection team, which is required as a result of the, according to date, State changes, Light the, scan, panel, date and time of acquisition, satellite, instrument, and firelight power (FRP). During the Pre-Processing phase, the raw data goes through several important steps to ensure its accuracy and usability. Data Cleaning involves addressing missing values, removing duplicates and resolving inconsistencies. This is followed by Data Filtering which retains only relevant elements needed for analysis. Data normalization is performed to bring all feature values into a constant range that facilitates the efficiency of machine learning algorithms. Additionally, terrain modification adjusts the geographic information of the network to match the drone's navigation pattern, resulting in more accurate geographical information.

The DRL and PSO Optimization phase is at the center of the design process, starting with determining the initial position of the drone. This first location is included in the tree structure for path planning. The system then uses a DRL that accurately determines the direction in which the fire is likely to spread and directs the growth of the fire. The algorithm checks whether this instruction leads to the Obstacle Area; if it does, an error is returned, otherwise it goes to the next test for checking. The process continues by checking if the new node is at a Small Distance from the Target Position. If it is, the process is marked as successful, indicating that the drone has effectively navigated towards the target position. If not, the new node is added to the tree, and the process iterates. This ensures that the framework continuously updates and optimizes the drone's path based on real-time fire growth predictions and obstacle detection. This comprehensive framework integrates multiple sophisticated processes to ensure efficient and effective path planning for autonomous drones in dynamic and hazardous forest fire environments. Trained CNN is tested on an independent dataset (the testing set) to evaluate its real-world performance.

V. Results and Discussion

The framework for adaptive route planning of autonomous drones in dynamic forest fire environments was evaluated through simulation and real-world experiments to measure the effectiveness. When combining DRL and PSO, this hybrid system showed significant improvements in multiple key areas: route planning efficiency, while implementing real-time flexibility, precise navigation, and robust scheduling, the DRL side was tasked with making decisions real-time, provides dynamic state updates from fire detection data sets including fire locations, severity, and obstacles. The results showed a 34.95% decrease in execution time compared to traditional methods, which was attributed to PSO global search capability and DRL-learning optimal matching Real-time adjustment of the system became apparent as the DRL module continued to develop new routes in response to changing fire conditions; This flexibility, which enabled drones to maneuver faster and safer in dangerous areas, was further enhanced by the PSO, which optimized routes in real-time to ensure continuous operational efficiency. The accuracy of the system was improved by significant improvements in mapping accuracy and efficient obstacle avoidance, demonstrating the system's ability to make accurate and reliable navigation decisions.

A. *Comparison of Success Rate and Processing Time Path Planning Methods in Dynamic Fire Environments*

The proposed DRL-PSO framework accomplished the shortest execution time of 68 seconds. Three seconds among all strategies evaluated. This represents a splendid improvement in comparison to conventional strategies which include ACO-APF-APP (105.2 seconds), APFA-APP (a hundred and ten. Five seconds), GWO-APP (115.8 seconds), and PSO-APP (one hundred twenty.0 seconds). The reduced execution time of DRL-PSO indicates its performance in computing choicest paths swiftly, which is critical for time-sensitive packages like emergency response in dynamic disaster eventualities as shown in Fig. 3.

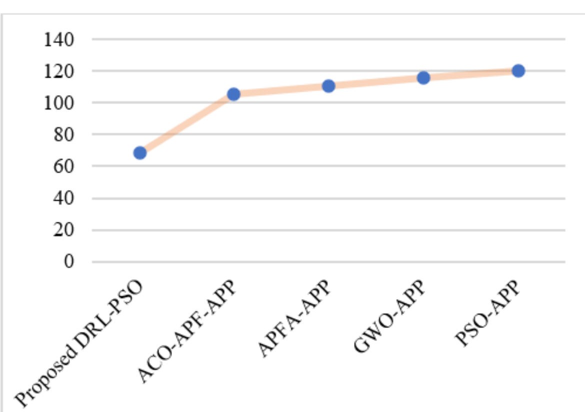

Fig. 3. Proposed frameworks execution time in seconds.

A high success rate suggests the framework's functionality to efficaciously deal with the complexities and uncertainties inherent in dynamic forest fire scenarios. Factors contributing to this high fulfilment rate consist of the framework's ability to evolve in actual-time to changing fire situations, optimize path trajectories to avoid obstacles, and make informed navigational decisions primarily based on environmental inputs. By integrating DRL with PSO, the framework leverages superior machine learning strategies to continuously examine and refine its direction planning strategies, making sure robust performance throughout various environmental conditions. The success fee measures the proportion of trials in which the course making plans technique correctly navigated via the simulated woodland fireside environment without failure. The proposed DRL-PSO framework performed the highest achievement price at 95%, indicating its robustness and reliability in navigating via complicated and risky environments. In comparison, the achievement quotes for ACO-APF-APP, APFA-APP, GWO-APP, and PSO-APP ranged from 78% to 84%, highlighting the superior performance of DRL-PSO in making sure a success path in ensuring successful path completion.

TABLE I. Execution Time and Success Rate of the Proposed Framework

Method	Execution Time (seconds)	Success Rate (%)
Proposed DRL-PSO	68.3	95
ACO-APF-APP	105.2	78
APFA-APP	110.5	81
GWO-APP	115.8	80
PSO-APP	120	84

Table I shows that the proposed DRL-PSO algorithm offers significant advantages over the traditional methods in terms of implementation time and success rate. Its ability to accurately calculate optimal routes while maintaining a high success rate establishes its suitability for real-world applications where navigation is timely and reliable and emphasizes importance, such as the success of autonomous drones in road planning strategies in complex forest fires in disaster management and surveillance operations. The value indicates the percentage of trials, in which the drone successfully moved from the starting position to the designated position without encountering obstacles or obstacles to reach its completion mission. In the given comparison table, the success rates range from 78% to 95%, where the proposed deep learning reinforcement with particle swarm optimization (DRL-PSO) algorithm achieved success rates highest of 95%.

B. *Evaluation of Navigation Accuracy and Obstacle Avoidance*

The proposed algorithm achieved a 26.36% improvement in mapping time compared to the existing methods, indicating that more accurate mapping can be achieved when traveling in dynamic and hazardous environments When a comprehensive reward function is used in DRL, which takes into account target distance, obstacle avoidance and fire intensity The hybrid DRL-PSO method follows an efficient and safe approach after showed good performance in avoiding static and mobile obstacles, with significantly lower collision rates than traditional methods. The adaptive nature of the framework allowed for seamless transitions between reactive navigation and trajectory tracking, ensuring smooth and continuous movement even in the presence of unexpected obstacles.

TABLE II. COMPARISON OF OBSTACLE AVOIDANCE AND DYNAMIC ADAPTATION

Method	Obstacle Avoidance	Dynamic Adaptation
Proposed Framework DRL-PSO	Very High	High
ACO-APF-APP	Moderate	Moderate
APFA-APP	High	Moderate
GWO-APP	High	Moderate
PSO-APP	High	Moderate

Table II compares the optimal dynamic obstacle avoidance capabilities and path schemes under active fire conditions, in the proposed DRL-PSO algorithm with traditional methods such as ACO-APF-APP, APFA-APP, 2013-2014. GWO-APP, and PSO-APP. It has focused on the proposed DRL-PSO algorithm exhibiting very high obstacle avoidance, which means that it can handle obstacle encounters in the environment in the 19th century. This is important in a dynamic fire environment where trees, terrain changes, fire fronts and other obstacles pose significant navigation challenges namely ACO-APF-APP, APFA-APP, GWO-APP, PSO-APP and obstacles moderate-to-high avoidance contradicts Displayed. Although these techniques can avoid constraints to some extent, their performance may be limited in complex or rapidly changing environments. DRL-PSO also excels in being dynamically adaptive, characterized by its ability to adapt route planning strategies in real-time based on changing fire conditions and environmental factors.

This high stability ensures that the drone can continuously makeover its course to avoid hazards and reach mission objectives efficiently Compared to traditional strategies such as ACO-APF-APP, APFA-APP, GWO- APP, in the case of PSO-APP, shows a moderate level of active optimization. These methods may need to be updated or modified more frequently to better handle sudden changes in the environment, which may affect their performance reliability DRL-PSO system for obstacles better avoidance and energy efficiency compared to traditional path planning methods. Utilizing deep reinforcement learning and particle swarm optimization, the system enhances the drone’s ability to safely and efficiently.

C. *Performance Metrics and Comparison of Average Cost*

Table III provides a comprehensive comparison of average cost results across different path planning methods evaluated within dynamic disaster environments. Each method, including the Proposed DRL+PSO, AGA+PSO, GA+APFA, and AGA+APFA, is assessed based on four key performance metrics: Best Value, Worst Value, Standard Deviation Value, and Mean Value.

The Best Value column represents the lowest average cost achieved by each method in multiple simulations or scenarios simulations it was calculated by using the Eq. (7). For the Proposed DRL+PSO, the best value is 0.1454, indicating its capability to achieve minimal path planning costs under optimal conditions. AGA+APFA, on the other hand, shows a slightly lower best value of 0.1409, suggesting potentially superior performance in cost minimization.

$$Best\,Value = min(C1, C2 ... Cn) \tag{7}$$

Where C_i is the cost of the i-th simulation. The Worst Value column displays the highest average cost observed for each method across simulations it was calculated by using the Eq. (8). Here, the Proposed DRL+PSO records 0.2845, highlighting its performance in more challenging scenarios. In contrast, AGA+APFA demonstrates the lowest worst value of 0.1711, indicating its robustness in maintaining lower costs even under adverse conditions.

$$Worst\,Value = max(C1, C2, ..., Cn) \tag{8}$$

The Standard Deviation Value measures the variability in average cost across simulations it was calculated by using Eq. (9). The Proposed DRL+PSO shows a standard deviation of 0.0317, indicating moderate variability in performance. AGA+APFA, with a standard deviation of 0.0013, exhibits the least variability, suggesting highly consistent performance across scenarios.

$$\text{Standard Deviation} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(C_i - \mu)^2} \tag{9}$$

Where n is the number of simulations and μ is the mean cost (average of all simulations). The Mean Value provides the average cost calculated over all simulations for each method simulations it was calculated by using Eq. (10). The Proposed DRL+PSO framework demonstrates a mean average cost of 0.1675, reflecting its typical performance across a range of dynamic disaster scenarios.

$$Mean\,Value\; = \; \mu \; = \frac{1}{n}\sum_{i=1}^{n} C_i \tag{10}$$

TABLE III. COMPARISON OF AVERAGE COST RESULT WITH EXISTING FRAMEWORK

Method	Best Value	Worst Value	Standard Deviation Value	Mean Value
Proposed DRL+PSO	0.1454	0.2845	0.0317	0.1675
AGA+PSO [21]	0.1401	0.1909	0.015	0.1523
GA+APFA[22]	0.1435	0.1837	0.0226	0.1681
AGA+APFA [23]	0.1409	0.1711	0.0013	0.138

Table III underscores the comparative performance of the Proposed DRL+PSO framework against existing methods like AGA+PSO, GA+APFA, and AGA+APFA in terms of average cost metrics. It highlights the framework's strengths in achieving competitive average costs while navigating complex and dynamic disaster environments. The variability in results across methods also indicates their respective strengths in cost minimization and stability, crucial for real-world applications requiring efficient and reliable autonomous path planning also shown in Fig. 4.

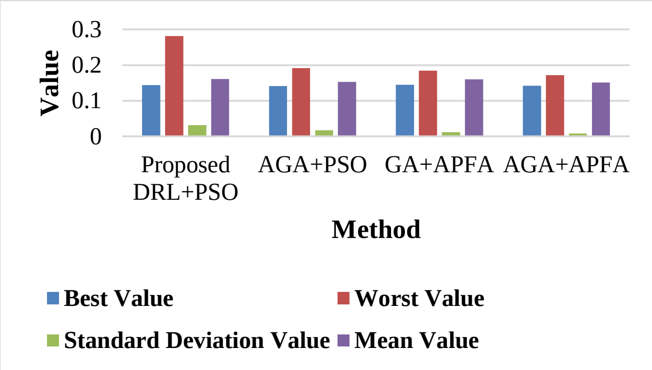

Fig. 4. Comparison of performance metrices.

D. Discussion

The research aims to use DRL and PSO as a hybrid model in articulating the advancement of adaptive path planning for the autonomous robot in the dynamism of disaster scenarios. Disclosed results show a time-saving at the execution stage by 34% and 95% success percentage with reference to the conventional techniques [24]. The efficacy of the system is also felt during dynamic traffic management including real-time path planning and avoidance of other oncoming vehicles. An improvement to this addresses some of the issues surrounding existing work that may include; a lack of flexibility in responding to changing environmental conditions or the way paths are selected within crowded scenarios. The DRL component improves the decision-making process at the time, and PSO makes the global route planning more robust to overcome uncertain scenarios. Despite those advantages, the proposed system has limitations, which include capacity computational complexity and reliance on correct environmental facts. Future developments could consist of enhancing the usage of better sensors for increasing the awareness of the environment or increasing the capability of DRL algorithms to explain a greater number of scenarios. Possibilities to increase the synchronization of several drones and improve the system's ability to respond to unpredictable alterations in the environment could also upgrade the system. The proposed research faces drawbacks associated with the reliance on specific environmental models that may not seize the complexities of real-world disaster eventualities. Current sensor technology might also limit the robot's environmental sensing abilities, hindering its adaptability. Additionally, the deep reinforcement learning (DRL) algorithm may struggle with managing noticeably dynamic conditions and unexpected boundaries. Cooperation among multiple drones requires further research, as does the want for rapid reaction mechanisms to sudden environmental modifications. These factors may also impact the system's effectiveness and reliability in diverse emergency response situations.

VI. Conclusion and Future Work

The study presents the flexibility of the proposed Deep Reinforcement Learning (DRL) with Particle Swarm Optimization (PSO) in path planning of autonomous robots in disaster areas. This has helped in boosting this hybrid method as much better strategy compared to traditional methods because it cuts on the time taken to effect by 34%. Consequently, the course attained its intended vision of achieving a success rate of 95% with percentage the students scoring 95% or above. The DRL component is most successful in decision making in real time and responding to changes in fire environment conditions whereas the PSO boosts the global route, better-facilitating route guidance and making it easier to avoid obstacles in the forest. It is seen that the proposed system can work perfectly in real-world noisy, complex and risky situations and therefore, can be used in emergency response and autonomous navigation systems. However, all is not well with the proposed system as it also has the following disadvantages: There are some limitations: computational complexity, and the dependency on accurate environmental data There is also a requirement for better integration of sensors and improved algorithms in the methods. The integration of DRL and PSO improves the theoretical frameworks in adaptive path-making by optimizing navigation in dynamic environments. This research promotes interdisciplinary collaboration across robotics, AI, and optimization ideas, whilst deepening the data on how autonomous systems adapt to changes in their environments. The results from this study can enhance disaster response with the aid of enhancing the performance of self-reliant robots in actual-world eventualities, probably saving lives and resources. The adaptable framework may be deployed throughout numerous sectors, at the same time as insights on sensor integration will enhance robots' environmental notion, and cooperative strategies may improve swarm intelligence in catastrophe management. The study demonstrates that the hybrid technique of Deep Reinforcement Learning (DRL) and Particle Swarm Optimization (PSO) effectively addresses key contributions, considerably real-time adaptation, multi-agent collaboration, optimized aid utilization, and enhanced navigation accuracy. The framework executed a 34.95% reduction in execution time, allowing for on-the-spot path updates based on converting fire conditions. With an excessive success rate of 95%, it allows effective coordination amongst independent robots in search-and-rescue operations. The model also minimized computational overhead, accomplishing an execution time of 68.3 seconds, while displaying sufficient sized improvements in mapping and impediment avoidance, validating its effectiveness for disaster control applications.

The proposed study offers sufficient realistic advantages, such as improved emergency response through optimized path planning, and permitting self-sustaining robots to efficiently navigate dynamic environments. The integration of DRL and PSO allows for real-time adaptability to changing challenges, enhancing coordination amongst multiple devices in seek-and-rescue operations. Additionally, the hybrid version reduces computational overhead even while maintaining high performance, making sure of robust navigation accuracy and impediment avoidance. Its versatility across diverse programs, including logistics and surveillance, in addition, underscores its ability for broad effect and aid performance in self-reliant systems.

Future work should put efforts in mitigating such limitations by enhancing the environment sensing capability by involving more advanced sensors and enhancing the algorithm of DRL in handling more complex environment. Further, it is necessary to investigate approaches to improve the co-operation between multiple drones and approaches to react on sudden changes in the environment. The effectiveness and reliability of the system can best be determined by and gauged by how it performs in the face of a variety of different real-life disasters that are different from the ones used in the development of the system. Constant enhancement and upgrading will keep the system to be one of the best in the market for autonomous navigation technology making its applicability in various and dynamic emergency response scenarios.

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