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AI Driven Approaches in Swarm Robotics - A review

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Abstract

The integration of artificial intelligence (AI) and swarm robotics has brought about significant advancements. Swarm robotics is based on decentralized control and self-organization, taking inspiration from natural swarms. It involves employing a large number of uncomplicated robots to collaboratively complete intricate tasks. The algorithms underpinning swarm robotics, which is artificial intelligence, vary depending on the specific role of AI - such as error detection, navigation, coordination, and optimization - and according to the tasks that these robots aim to undertake. In this systematic review, we aim to explore algorithms based on artificial intelligence in swarm robots and the advantages of applying them in the real world. In this systematic review, 74 scientific papers published between the years 2020 to 2024 were examined, but 53 of them were included after applying our methodology to them. The review investigated the common role of AI in swarm robotics, the most commonly used AI algorithms, and the percentage of the research that was conducted and tested in the real world. In conclusion, we discovered that there is a need for research that develops fault detection and coordination strategies, as well as a need for real-world testing.

Keywords: AI Algorithms, AI in Swarm Robotics, AI Roles, Robotics Real-World Scenarios, Swarm Robotics.

1. Introduction

Artificial intelligence is an advanced technology used by machines and computers that enables them to simulate the intelligence and capabilities of humans in solving problems and performing tasks. This technology is trained on a huge amount of information that makes it perform well. AI is currently widely used in many different technologies, for example, makes it easier and faster to implement routine and repeated tasks, especially if time is a crucial component of performance efficiency. Swarm intelligence is a novel form of AI that emerged in the middle of the 1980s and was modeled by the biological intelligence of living things, including swarms of locusts, ants, and bees [1]. Humans have been inspired to create robots with systems that function similarly to swarms of live things by seeing their collective behavior in swarms. These swarms are able to perform tasks that individuals are unable to complete because of their ability to coordinate and develop precise, complicated actions [2]. Swarm robots comprise a vast swarm of individual robots that collaborate to complete a specific task, such as defense, surveillance, or search and rescue, that may pose a risk to humans or take a long time. By sharing tasks and cooperating, swarm robots are able to solve problems more quickly and effectively than they could individually. Robots in a swarm are better and have a lot of advantages over individual ones. Further, compared to individual robots, swarm robots are more reliable, scalable, and dependable [3]. Swarm robots have many uses in various fields, and they are almost indispensable in some of them. Examples of their use include in medicine, such as surgeries, monitoring the health of patients, and treating cancer cells. In the environment, such as mining, geological surveys, and cleaning oil spills. In addition, agriculture foraging, harvesting, search and rescue, military activities, painting, and many others [3].

Error detection, optimization, navigation, and coordination comprise the majority of the applications of artificial intelligence and their roles in swarm robots.

We will concentrate on these roles in this research, and as these are the most prominent and recent AI roles, scientific research papers have been categorized according to them. Along with examining the benefits and impacts of their practical implementation, this study will introduce the various algorithms utilized in the four AI functions of swarm robots.

The following research questions are presented in accordance with the previously stated objectives of this paper:

RQ1: What are the uses of AI in swarm robotics?

RQ2: What are AI algorithms used for swarm robotics?

RQ3: What are the practical implications and advantages of employing real-world applications in the domain of swarm robotics?

The methodology used in this systematic review included only research that matched the criteria that had been identified. After excluding research that did not meet the criteria, the number was 53 scientific research published between the years 2020 and 2024. There are more details about our methodology that were mentioned in Section 3. After analyzing scientific research, it was concluded that the majority of research is centered around studying optimization, one of the roles of artificial intelligence, and that there is a need to study coordination and especially error detection since it has the lowest percentage. In addition, there is a lot of research that used simulation for its results, while the percentage of research that was implemented in the real world was small. We also discovered that there are 5 algorithms of swarm robots used commonly in research, which are: Reinforcement Learning (RL), Particle

Swarm Optimization (PSO), Genetic Algorithms (GA), Artificial Neural Networks (ANNs), and Deep Reinforcement Learning (DRL).

The remainder of the paper is structured as follows. Section 2, describes the methodology used in this review. Section 3, presents a summary of scientific research papers on swarm robots and classifying them according to the AI role. Section 4, displays the results of our research and answers the research questions. Section 5, concludes the work and proposes future research.

2. Methodology

This systematic review aims to explore AI-driven approaches in swarm robotics, specifically focusing on three research questions mentioned in the previous section.

To ensure a comprehensive collection of relevant literature, a systematic search was conducted across multiple databases, including Google Scholar, ScienceDirect and IEEE. Search terms included “swarm robotics”, “robots swarm” and “AI in swarm robotics”. The search covered research articles published between 2020 and 2024 to capture the most recent advancements in the field. Studies were included if they were scientific research articles with full text provided and written in English language and details about the AI techniques used with a swarm or group of robots are included, Articles that provide examples of AI algorithms applied in swarm robotics or discuss their real-world applications.

The three reviewers of this study examined up to 74 published research articles and filtered them exhaustively to meet the systematic literature review framework criteria. Studies were excluded when it is not related to artificial intelligence in swarm robotics, not in English, published before 2020, or didn’t include details about the used AI method or algorithms. The result after analyzing and filtering the collected studies was only 53 scientific research articles which are included in this study. The review indicates four AI roles for swarm robotics which are: swarm navigation, swarm coordination, swarm optimization, and swarm fault detection.

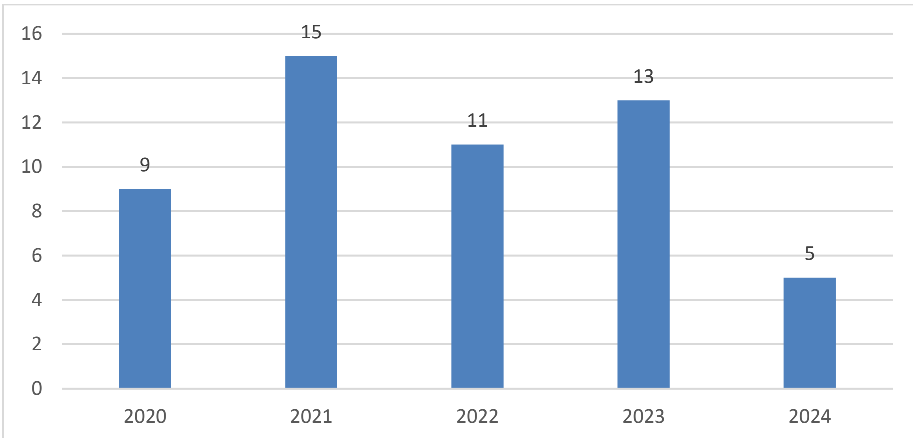

Fig. 1. Count of published papers.

3. Literature Review

AI-driven approaches in swarm robotics have gained significant attention in recent years and have been leveraged in many applied areas of life. It leads to fast operation time and effective achievements. Here is a highlight of some recent research that explored various techniques and models for enhancing navigation, coordination, optimization, and fault detection in the field of robot swarms.

3.1 Navigation

[4] Provides a summary of recent work and an overview of the trend in the use of AI algorithms for path planning problems with unmanned aerial vehicles (UAVs) swarms. The AI techniques included in the review were categorized into four main groups: reinforcement learning techniques, evolutive computing techniques, swarm intelligence techniques, and graph neural networks. The review shows an increase in publications in recent years and a change in the predominance of the most widely

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used techniques. The research emphasizes the importance of cooperative behavior and communication constraints in achieving superior performance in planning tasks for swarms of robots.

Path planning for (UAVs) have has studied by many researchers, [5] discussed a path planning optimization problem that aims to maximize the amount of collected data while taking into account realistic constraints. In the implemented scenarios, multiple UAVs were involved and it operated independently without any communication or information-sharing. Additionally, the number of UAVs present in these non-cooperative situations may vary randomly. Double Deep Q-Network with Dueling Architecture (D3QN) algorithm was developed to learn the decision-making policy for the typical UAV, without any prior knowledge of the environment. The algorithm is tested in experiment scenarios with different numbers and positions of IoT nodes and UAVs showing that the algorithm can navigate in real-time with a high success rate, high data collection rate, and low collision rate.

Another research by [6] proposed an algorithm called Deep Learning Trained by Genetic Algorithm (DL-GA), which combines the advantages of deep learning and GA for multi-UAV path planning for faster optimization in challenging scenarios. The evaluation of DL-GA was based on the total distance of UAVs, the required number of UAVs, and solving time. (DL-GA) showed a much faster solving speed compared to the Genetic Algorithm (GA) alone. Also, it maintains a high optimization capacity, almost matching GA, and even outperformed GA under certain conditions. The research demonstrates the effectiveness of DL-GA through experiments, suggesting it is a promising approach for multi-UAV path planning.

[7] introduces a new method for multi-UAV to plan paths together using deep reinforcement learning helping it map desired areas faster than before. Cooperative behavior and communication constraints are emphasized as important factors for

superior performance in planning tasks. the method was also tested in a real situation with computer-made data where a swarm of drones checked the temperature of the ground from the sky. The method works well even when the number of drones changes or they can't communicate much without the need for new training.

[8] research presents a defense approach aimed at guarding a protected area against an attack by a swarm of adversarial agents in three-dimensional space. In the Methodology, the paper introduces a new method for 3D StringNet herding and extends previous 2D herding control laws. The results highlight the effectiveness of the proposed approach in quickly forming defenders and generating algorithms for determining the minimum number of defenders required for 3D formations.

A framework for controlling robotic swarms through a combination of mean-field control, reinforcement learning, and collision avoidance algorithms was proposed by [9]. This approach exceeds standard multi-agent reinforcement learning and enables decentralized open-loop control.

A protective mechanism based on the behavior of bees and clarifying its efficacy through a multi-agent model employing decision-making mechanisms was proposed by [10]. The results point out that the mechanism is effective in reaching an agreement and decreasing decision-making time. Notable strengths of the paper include its novelty, experimental verification, and clear methodology.

Precise UAV system modeling is made possible by the ROS-NetSim framework presented by [11], which also makes cooperative simulation possible, which greatly improves performance and lowers positioning errors. The work shows significant progress in UAV-based synthetic apertures and highlights their potential uses by utilizing a co-design approach and adding an FTM range.

When it comes to target-driven visual navigation tasks, the DIRL approach presented by [12] which combines Deep Reinforcement Learning with Imitation Learning—

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performs better than traditional deep reinforcement learning techniques. Simulation experiments in the AI2-THOR environment show that the strategy improves sample efficiency and navigation performance by utilizing both IL and DRL. The study, however, doesn't go into detail about how to use it in real-world situations.

The study [13] examined how well off-road navigation for robots may be enhanced by using linguistic commands, landmarks, and preferred terrains. Through the use of a speech-to-text model and the incorporation of preferred terrains and adverbs into instructions, navigation performance was much enhanced and errors were reduced. The study lacked a thorough discussion of scalability and practicality, despite the encouraging results, suggesting that more testing and verification are required to determine the model's generalizability.

To support sim-to-real transfer for robotics visual navigation, the study [14] presents SEER, a structured representation including navigability and depth data. Control policies trained in simulation can now generalize well across a wide range of contexts thanks to SEER, which dramatically outperforms current methods in bridging the domain gap between simulated and real-world environments. Although SEER exhibits encouraging outcomes, its dependence on simulated environments might present challenges in fully capturing all potential scenarios, hence requiring additional investigation and improvement to ensure strong real-world implementation.

The authors of this paper [15] present a novel approach to researching the target search of robot swarms by integrating simulated and real robots. This paper specifically focuses on combining artificial potential fields with mechanical Particle Swarm Optimization (mechanical PSO). The results demonstrate the effectiveness and robustness of the proposed search method in achieving multiple targets for swarm robots. However, it’s important to note that the findings may face challenges related to localization errors and accuracy.

The authors in the paper [16] used an Automatic Modular Design approach called AutoMoDe. The study evaluated different exploration schemes, and the chosen schemes were found to meet the specific mission requirements. The method's strengths include its ability to explore a larger search space, resulting in more effective fulfillment of mission requirements.

In 2021, the paper [17] utilized the Particle Swarm Optimization (PSO) algorithm Angle of Rotation (AoR) and Memory (Mem) in their toolkit. The experimental results demonstrated the algorithm's effectiveness as a swarm of robots successfully solved search problems in both simple and complex environments. The proposed method achieved a high success rate (100%) across different environment sizes, reflecting the nature of swarm intelligence. It also exhibited high efficiency in solving mazes of varying complexity levels and locating targets reliably within a reasonable time. However, it showed Sensitivity of algorithm parameters can impact performance.

The authors in the paper [18] employed a Multi-Agent Deep Deterministic Policy Gradient algorithm (MADDPG) with Reinforcement Learning (RL). The paper aimed to investigate how human scientists assign primary tasks to robots and multi-robot systems to explore unknown Mars surfaces. The results showed better efficiency than traditional deep RL algorithms in a collaborative multi-agent exploration environment. The proposed method is effective for collaborative space exploration, offering an alternative solution to the risks and costs of a single explorer. However, a potential weakness is identified: as the scale of the multi-agent system increases, the proposed optimizer may show reduced performance in mean episode rewards.

The paper [19] introduces a methodology using fully autonomous drones with various modules to facilitate experiments such as trajectory planner, trajectory-broadcasting network, probabilistic mapping, drone removal module, VIO-based localization module, controller module, and planning module. These hardware modules facilitate comprehensive experimentation using a custom-designed micro-platform assembled by the researchers, with their dataset available online. The effectiveness of the proposed planner is evaluated through real flights and simulations, as well as real-world experiments. Notable strengths include obstacle and collision avoidance but identified weaknesses include complexity in temporal optimizations and limited decision variables.

The paper [20] explores new methods for improving robotic navigation, focusing on social interaction and reducing user intervention. It uses genetic algorithm optimization techniques to enhance the robot's adaptability to social conditions and avoid collisions in dynamic environments. To simulate human walking behavior, it utilizes the actor model from Gazebo for a more realistic evaluation process. However, increasing environmental complexity may pose challenges and limit scalability, necessitating further research in this area. Overall, this research offers valuable insights into AI-driven approaches for enhancing robot navigation in human-centric environments.

The paper [21] presents an innovative approach to the classic game of Tic-tac-toe, utilizing a swarm of nano-UAVs driven by a Reinforcement Learning (RL)-based algorithm. The methodology revolves around the implementation of this RL algorithm to enable the nano-UAVs to play the game interactively. The study shows how combining swarm robotics and reinforcement learning can make interactive and engaging experiences. Additionally, the researchers conducted a questionnaire-based survey to collect feedback from participants regarding their experience with the game. Results indicate a high level of excitement and engagement among participants, particularly in response to the RL algorithm's performance. However, the study highlights the limitation of small sample size and the possibility of biases in participant feedback.

3.2 Coordination

[22] presents a hybrid machine learning method to learn how individual robots can control themselves by watching swarm behavior. The used method called knowledge-based neural ordinary differential equations (KNODE) which combined artificial neural networks with known agent dynamics. Testing showed that controllers worked well in both 2D and 3D environments and could handle larger swarms. The approach has been proven to be efficient and scalable for robot swarms since it does not need detailed action data and can work with large groups of robots.

A study of speeding up the process and finding good robot group setups that worked well in new situations was performed [23]. Surrogate models based on Gaussian processes and artificial neural networks to predict robot behavior were proposed where a hybrid evolutionary algorithm combining a genetic algorithm and a local search for optimal robot configurations. A simulation tool was used to test and validate the robot swarm formations by the researcher where the optimized robot formations were stable in a majority of new, unseen scenarios.

In the research of [24], a hardware module was designed and introduced that enables swarm robots to locate each other and communicate through audio. The used model was AudioLocNet, which is ais a deep neural network (DNN) designed to localize sound sources using three convolutional neural networks (CNNs). With the help of its deep learning module, it was capable of performing localization in challenging environments, such as those with non-line-of-sight and reverb. To support concurrent transmission, it uses orthogonal audio chirps and has an audio message frame design that balances localization accuracy and communication speed.

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AI's ability to maintain formation and coordinate autonomously in challenging environments and the potential of neuro-evolutionary algorithms called Hill Climb Assembler Encoding for underwater vehicle swarms are highlighted by [25]. A neural control system is introduced where the leader vehicle guides followers using information from sonar and cameras to avoid obstacles, while followers follow the leader in a specific formation and avoid each other, the leader, and obstacles detected by the leader. The approach was tested in simulated underwater conditions, paving the way for sophisticated underwater exploration and monitoring tasks with high autonomy and minimal collision risk.

The study of [26] examines the development of self-coordination and communication in a computer-simulated ant colony using spiking neural networks through an evolutionary optimization process. By utilizing SNNs, the Electrophysiology Analysis Toolkit, and the L2L framework in the methodology, it is demonstrated that pheromone-based communication improves the foraging performance of ants. The paper effectively shows how self-coordination and communication can emerge under the control of SNNs.

To manage the density of robotic swarms within a certain spatial region, the study of [27] presents a mean-field feedback control technique, and the simulation shows its effectiveness. The study advances knowledge of swarm control problems and makes use of weak solutions to streamline system analysis by providing a concise description of the control strategy and robustness analysis. To determine the paper's practical applicability and scalability, more empirical validation in various contexts and with different swarm sizes is required.

In 2021, a study [28] utilized Deep Learning (DL) technology to develop a pairwise interaction model for real fish interactions and integrated the model into the collective motion control of multi-agents across different scales. The methodology involved using a Deep Neural Network (DNN) model. They propose a novel key neighbor selection strategy, which is called the Largest Visual Pressure Selection (LVPS), the individual uses the properly trained DNN model for the pairwise interaction. The result shows simplicity, broad applicability, and computational efficiency. The proposed method can predict collision avoidance capabilities. The dataset used in this study is experimental data of collective motion on Hemigrammus rhodesterus fish.

In the paper [29], the authors used a 6-PPSS redundant mobile platform and included an Extended Kalman Filter routine. They also applied a variant of the crawling probabilistic road map motion planning algorithm. The model used is inspired by how insects move objects around while avoiding obstacles. The study showed that a robotic swarm carrying a load could successfully move through cluttered space. The use of the Extended Kalman Filter was effective in reducing estimation errors in relative locations, especially when position information is shared among agents, but it was noted to be impacted by location uncertainty and sensor noise.

The study [30] proposes a new model that integrates synchronization and swarming for coordination in both time and space. It utilizes a time-discrete swarm aggregation model and specific functions that combine this spatial model with a discrete temporal coordination model, resulting in a discrete spatio-temporal coordination model. It focuses on low-update-rate coordination across space and time. The research validates the model in both simulation and real-life scenarios using real small robots and drones. This model enables robust multi-robot coordination, which is crucial for applications requiring accurate timing and spatial arrangements.

A study conducted by [31] has developed a control method that employs AI techniques to help robots maintain formation while tracking a dynamic target. The study tested this approach in real-world settings with robots on wheels. The results were quite promising, as this method proved to be highly effective even under unpredictable conditions. These findings highlight the adaptability and reliability of the designed control strategies in managing complex dynamic environments, particularly in the fields of farming, surveillance, and space exploration.

A study by [32] highlights the potential of neural networks in advancing autonomous robotic systems it investigates how robots can learn to coordinate and communicate effectively through imitation learning algorithms and training neural networks for task-specific interactions. By utilizing communication strategies in robot swarms, their performance can be improved, allowing them to make decisions almost as well as an expert controller with full knowledge of the environment. The evaluation was conducted in a simulated environment using Enki, a fast and powerful simulator, demonstrating that communication between robots significantly enhances their decision-making capabilities, mirroring the performance of a central controller.

The paper [33] explores social learning through distributed online reinforcement learning and machine learning (ML) techniques. The research did not specify a particular dataset, learning begins when robots are deployed in real-life scenarios. It focuses on the implementation of social learning for swarm robotics, emphasizing local communication between robots. However, it is limited by its focus on real-life conditions rather than a controlled environment, which hinders the ability to isolate and analyze specific variables.

The paper [34] explores the use of a swarm of robots to assist and protect migrants in challenging environments. The methodology involves a coordination algorithm that combines convolutional neural network (CNN) and fuzzy logic. Experiments were conducted using a dataset of 405 pictures obtained from the data provided by the IMU. The results offer valuable insights into aiding and safeguarding migrants within complex environments, showcasing high precision and recall rates for the

CNN model, allowing it to adapt to various situations. However, limitations such as the lack of real-world testing and difficulties in geo-localization are noted, suggesting areas for further research and improvement.

3.3 Optimization

[35] presented real-time locust management and crop protection using a swarm drone system for object detection and targeted pesticide spraying. A model for image recognition was designed using the YOLOv8 algorithm. a dataset of images of locusts collected and used to train the model. The research tests showed that AI and drone technology can significantly reduce crop damage caused by locusts exposing promise for sustainable agriculture.

[36] discusses a study that integrated swarm intelligence with deep transfer learning for UAV image classification. The study has used the RetinaNet model for feature extraction, and a cascaded long short-term memory (CLSTM) model has been applied for classifying aerial images, resulting in enhanced classification accuracy. A wide range of simulations have been implemented to ensure the model's performance. The model is suitable for real-time environments and can be used for tasks such as vegetation mapping and disaster management.

A possible solution to the problem of limited on-board computation in UAVs which makes it difficult to process complex models has been proposed by [37]. The solution involves distributing image classification tasks among a group of UAVs, enabling quick image recognition and faster decision-making. The proposed system model uses a swarm of UAVs for real-time image classification, employing Convolutional Neural Networks (CNNs) with different structures. The solution also includes an online heuristic solution to improve latency by efficiently placing layers among UAVs in CNNs. The proposed model outperformed the online solution, delivering better and faster results.

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[38] introduces and verifies a defensive approach known as "Multi-Swarm StringNet Herding" developed to confront adversarial swarms with a group of defenders. The methodology develops and validates a decentralized version of the Mixed-Integer Quadratically Constrained Program to effectively allocate defenders to identified attacker swarms. The results show that this method enhances the original "StringNet Herding" technique, allowing defenders to guide all attackers towards a secure area even when they divide into small swarms.

A new cooperative foraging behavior model based on pheromones for swarm robotics, utilizing a dynamic wave expansion neural network (DWENN) presented by [39]. The results highlight the model's capability to create resilient, adaptable, and scalable self-organizing behaviors among numerous robots, achieving efficient foraging with just two second waiting time.

To achieve a reliable formation under different initial conditions, [40] Focus on evolutionary optimization for determining swarm parameters like inter-robot distance to ensure stable formations using Genetic Algorithm (GA). The method's robustness was tested in realistic simulations which is ARGoS3 simulator, and real scenarios using E-Puck2 robots. Experiments prove effective in maintaining desired formations under diverse conditions. The inclusion of real robot validations illustrates the method's applicability in practical settings, enhancing the self-organization capabilities of robotic swarms.

To enhance decision-making and path-planning efficiency for a group of robots, [41] Developed a novel quantum computing approach inspired by how ants find food. The method showed faster convergence and scalability in various swarm sizes compared to traditional models, indicating significant advancements in computational efficiency and potential for complex task applications like search and rescue. IBM Quantum simulator was used to test the quantum-based path-planning algorithm and NetLogo and a Java-based simulator to model ant behavior in simulations.

[42] develops a new model combining multiple AI techniques to enhance surveillance tasks in swarm robotics. Integration of Genetic algorithms, Cellular automata techniques, Inverted pheromones from ant colonies, and Tabu search was introduced by the researchers. An evaluation Testing with e-Puck architecture in in Webots simulation environment showed that the model excelled in reducing computation costs and navigating complex environments demonstrating the effectiveness of hybrid AI strategies in real-world applicable simulations for improved surveillance efficiency.

In [43] using datasets gathered from the ARGoS simulator, ensemble learning models—specifically, Boosted Trees and Bagged Trees—have proven to be more accurate than more conventional machine learning methods in predicting the speed of swarm motion. Their scalability further demonstrates their robustness across a range of swarm sizes, which guarantees precise forecasts under various circumstances, including those involving barriers.

In [44] the decentralized ergodic formulation for swarm control shows robustness against real-world problems including hardware failures and communication breakdowns. Testing shows that the system responds to user commands and environmental inputs efficiently by integrating dynamic task adaptation with ergodic planning.

The complex behavior of bees was effectively simulated by the genetic algorithm-based model presented by [45], which reproduced both the macro collective activity and the local body dynamics. Although the model did not achieve a perfect match with the real data, it did show realistic bee trajectories and offered insightful information about bee behavior. Further study and improvement will still be needed

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to fully capture the complex motion dynamics and low-aligned, noisy behavior of bees.

For trajectory tracking control of Cable-Driven Continuum Robots (CDCRs), the paper [46] suggests a Fractional-Order Proportional-Integral-Derivative (FOPID) controller optimized by Particle Swarm Optimization (PSO). Simulation results show that the FOPID controller works well for CDCR trajectory tracking, producing smoother control signals and better tracking accuracy when compared to optimized and conventional PID controllers. However, the investigation of real-world implementation issues is necessary.

[47] proposes a Swarm Deep Reinforcement Learning (SDRL) method based on blockchain to enhance robotic manipulation learning speed and utilize data sharing among robotic agents. The decentralized approach allows individual robots to learn faster and the integration of blockchain technology provides a unique approach to privacy and data integrity in swarm learning environments. The model was tested in simulation using OpenAI Gym's MoJoCo simulators. Additionally, the proposed SDRL scheme was evaluated using real robots proving its performance and efficiency.

A new Particle Swarm Optimization algorithm, called Adapted Particle Swarm Optimization (PSO) was successfully developed by [48]. The proposed algorithm is a revised version of PSO that is specifically designed for controlling robotic swarms by considering the robots' physical capabilities like speed and how quickly they can speed up or slow down and avoid crashing into things to improve navigation and survivability in obstacle-rich environments. Testing was demonstrated through MATLAB and Gazebo simulations showing better performance in guiding robots through difficult areas.

In the paper [49] the authors employed the Robot Bean Optimization Algorithm (RBOA) within the context of Swarm Unmanned Aerial Vehicles (UAVs). The results obtained from search simulations show that the RBOA performs better than other approaches. Its strengths include fast and effective search capabilities, distributed collaborative interaction, and swarm intelligence emergence. However, it is mainly suitable for scenarios with smaller numbers of robots due to its focus on solving a single-target searching problem.

The paper [50] presents a methodology that uses an automatic modular design approach, namely AutoMoDe-Cedrata and AutoMoDe-Maple. However, the paper does not specify a particular dataset. The outcomes indicate that the suggested modules allow for the development of efficient behavior trees for robot swarms. The strength is the efficacy of AutoMoDe-Cedrata in producing control software for robot swarms. However, a weakness in Cedrata's is the difficulty in automatically generating control software with performance comparable to human-designed software, particularly when communication capabilities are required.

The paper [51] introduces an innovative approach to contractor selection by applying AI techniques based on the PSO algorithm. The methodology involves collecting real-world data on contractors, including cost, quality, and time performance. The study utilizes a dataset available online to train and validate the AI-driven PSO method. The results highlight the effectiveness of this approach in achieving optimal contractor selection, offering valuable insights for project managers and stakeholders involved in the process. Notable strengths of the study include its use of real-world data, enhancing the relevance and applicability of the findings.

The paper [52] introduces a novel approach to generating collective behavior in multi-legged robotic swarms. focuses on employing the Proximal Policy Optimization (PPO) algorithm to generate collective behavior in a multi-legged robotic swarm. The methodology involves utilizing deep reinforcement learning within the PPO framework to design controllers for the robotic swarm. Through computer simulations, the study illustrates the effectiveness of PPO in generating collective behavior and designing robot controllers capable. However, the study highlights the limitation of lacking experimental validation in real-world scenarios.

in 2024, The paper [53] delves into the transformative potential of swarm intelligence in revolutionizing electric vehicle (EV) technologies. The study introduces an intelligent control framework that integrates conventional EV control techniques with swarm robotics principles, Results show that electric cars driven by swarm algorithms exhibit remarkable adaptability, effective navigation, and energy optimization capabilities. This underscores the flexibility and optimization prowess of swarm robotics in managing electric vehicles. Furthermore, the study underscores the significance of robust communication protocols, efficient algorithms, and the validation of findings through practical experiments, emphasizing the importance of ensuring the reliability and applicability of swarm-driven electric vehicle technologies in real-world scenarios.

The paper [54] published in 2023, introduces a novel methodology to address the optimization challenge of routing robot swarms within sorting centers. By utilizing a multi-agent event-based simulation framework coupled with an event-driven architecture known as COS.SIM and integrating the Dijkstra algorithm. The researchers conducted experiments using their own dataset available online. Results indicate that the introduced approach achieves fast convergence to high-quality solutions, and outperforms the current state-of-the-art algorithms

The paper [55] focuses on optimizing communication, energy transfer, and control for underwater robots. The researchers utilized magnetic induction for communication and wireless energy transfer. Results showed that wireless charging underwater is possible and their methods effectively maintained network integrity while efficiently transferring energy for the robots' tasks. Their solutions were praised for keeping the network strong and transferring energy well, but they noted that their approach might not work as well for larger groups of robots.

3.4 Fault detection

The use of real robots underscores the practicality of swarm robotics systems in real environments, showing the potential for AI strategies in fault detection and adaptability. An evolutionary algorithm to optimize swarm parameters for a swarm of autonomous robots self-organizing proposed by [56] where a Genetic Algorithm (GA) and a Local Search algorithm (LS) were used as part of a High-level Relay Hybridization (HRH) approach to find the best solutions for robot formation. An evaluation was applied by the researchers using the ARGoS simulator and E-Puck2 Real-world robots where the proposal was successfully validated and demonstrated high fault tolerance and the capability to rebuild formations effectively.

4. Discussion

In the Discussion section, we thoroughly examine the findings obtained from this review on AI-driven approaches in swarm robotics, Addressing the core research questions related to the application of AI in swarm robotics, AI algorithms employed, and the advantages of using them in real-world scenarios with the aim to uncover any gaps that require further exploration.

After extensive filtering and analysis, 53 scientific research articles were included in this study. The review found that AI plays four key roles in swarm robotics: swarm navigation, coordination, optimization, and fault detection. These roles enhance the capabilities of robot swarms in different applications.

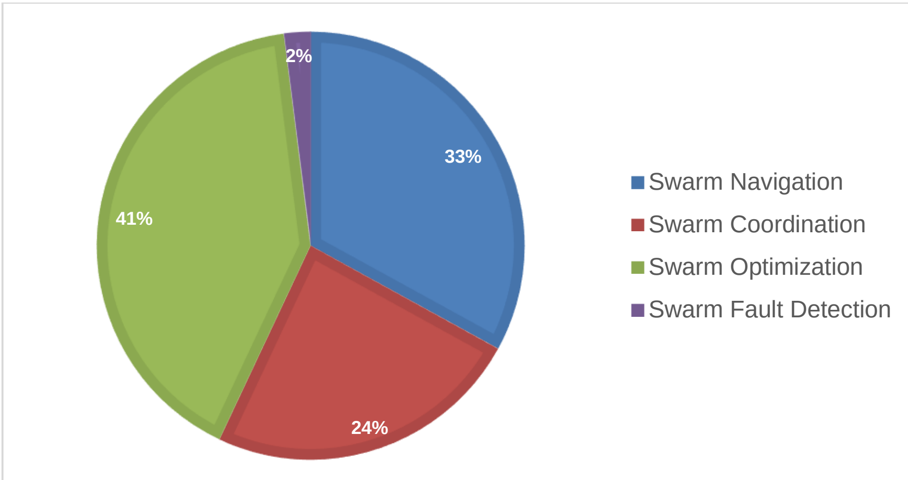

Fig. 2. AI roles included in research papers.

The distribution of AI roles in swarm robotics, as identified from the included studies, is depicted in Fig. 2 Optimization 41% emerged as the most prevalent, followed by swarm navigation 33% and coordination 24%. Additionally, only 2% accounted for swarm fault detection. The review emphasizes the importance of AI-driven optimization techniques in maximizing efficiency and performance but also highlights the need for further research and development in navigation and coordination to ensure robust behavior in real-world applications.

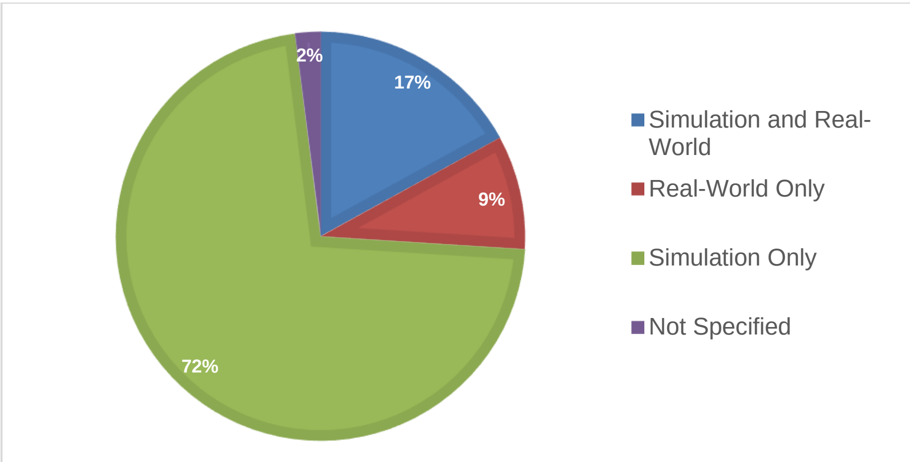

Fig. 3. Types of testing environment in research papers.

The testing environments utilized in the included studies are shown in Fig. 3 The study found that 72% of the research employed simulations, 17% utilized a combination of simulation and real-world scenarios, and 2% did not specify any testing environment. Moreover, 9% of the studies conducted experiments only in real-world scenarios.

Research Question (RQ1) aims to explore the application of artificial intelligence in swarm robotics. The review identified four main roles of AI in this field: swarm navigation, coordination, optimization, and fault detection. These roles enhance the capabilities of robot swarms in different applications.

1. Swarm Navigation: AI facilitates the movement of robot swarms around obstacles and navigation within their environment.
2. Swarm Coordination: AI empowers robots to collaborate and synchronize their actions without centralized control.
3. Swarm Optimization: AI algorithms assist robot swarms in optimizing performance and efficiently accomplishing tasks.
4. Swarm Fault Detection: AI systems can identify and resolve issues within a

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robot swarm, ensuring smooth operation.

These applications of AI play a crucial role in enhancing the capabilities and performance of robot swarms across diverse tasks and environments.

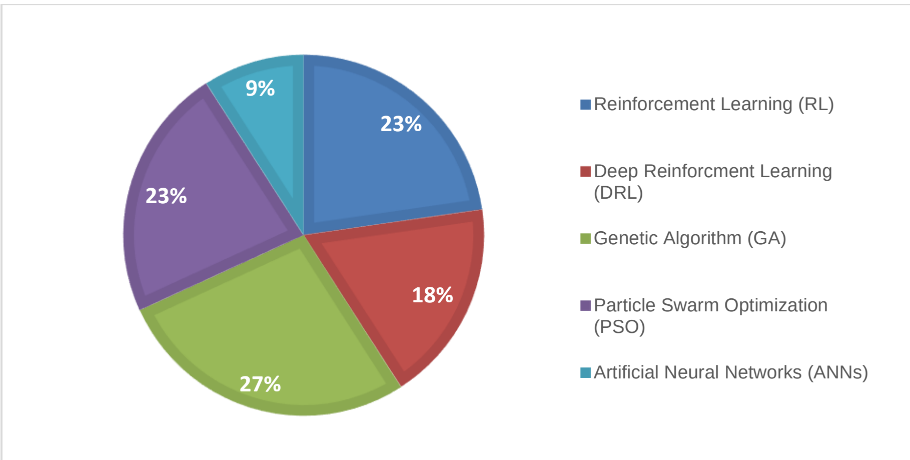

Fig. 4. The most common AI Algorithm used for swarm robotics.

Research Question (RQ2) investigates the specific AI algorithms employed in swarm robotics. Fig. 4 shows the most common AI algorithms used for swarm robotics as identified by this review which include:

1. Reinforcement Learning (RL) Algorithms: enable robots to learn optimal behaviors through trial and error.
2. Particle Swarm Optimization (PSO): Guides robots to find optimal solutions for tasks like path planning.
3. Genetic Algorithms: Evolve robot behaviors and strategies based on genetic variation.
4. Artificial Neural Networks (ANNs): ANNs are utilized for learning complex mappings between sensory inputs and motor outputs, enabling robots to adapt their behavior based on experience and feedback.

5. Deep Reinforcement Learning (DRL): DRL combines reinforcement learning with deep neural networks to enable robots to learn complex behaviors directly from raw sensor data, without the need for explicit programming.

These algorithms enable robot swarms to adapt and optimize their behavior in complex environments, enhancing their overall performance.

In Figure 4, the most prevalent algorithm is Genetic Algorithms (GA) at 27%, followed by Particle Swarm Optimization (PSO) and Reinforcement Learning (RL) algorithms, each at 23%. Deep Reinforcement Learning (DRL) is 18%, Moreover Artificial Neural Networks (ANNs) represent 9% of the utilized algorithms. These findings highlight the prevalence of these AI techniques as identified by this review. Additionally, Table 1 displays further algorithms identified within the scope of this study.

Research Question (RQ3) aims to understand the practical benefits of applying swarm robotics in real-world applications. Some potential benefits include:

1. Improved Efficiency: Swarm robotics can complete tasks like search and rescue more quickly and effectively than traditional methods.
2. Enhanced Exploration: Swarm robotics enables efficient exploration of unknown or hazardous environments, such as disaster zones, space, or underground mines, where human access is limited or unsafe.
3. Adaptive Response: Swarm robotics systems can dynamically adapt their behavior and strategies in response to changing environmental conditions or task requirements, ensuring robust and flexible performance.
4. Collaborative Problem-Solving: Swarm robotics fosters collaborative problem-solving by leveraging the collective intelligence of multiple robots, allowing for the efficient completion of complex tasks that exceed the capabilities of individual agents.

These benefits highlight the potential of swarm robotics to address real-world challenges effectively and efficiently.

In Table 1, we provide a summary of the papers included in this review, outlining the AI role, testing types (simulation and real-world), and the corresponding algorithm/model name. This concise overview facilitates a comprehensive understanding of the diverse applications of AI in swarm robotics, alongside the testing environments and specific methodologies employed across the studies.

Table 1. Summary of the Papers Included in this Review.

Reference	AI Role	Testing type		Algorithm / model name
		Simulation	Real-world	
[4]	Navigation	-	-	Not specified
[13]		-	√	Large language model (LLM)
[21]		-	√	RL algorithm
[5]		√	-	Dueling Double Deep Q-Network (D3QN)
[6]		√	-	Deep Learning Trained by Genetic Algorithm (DL-GA)
[8]		√	-	3D StringNet herding
[10]		√	-	Decision-making mechanisms
[12]		√	-	Deep Imitation Reinforcement Learning (DIRL)
[17]		√	-	Particle swarm optimization (PSO) algorithm
[18]		√	-	Multi-agent deep deterministic policy gradient algorithm (MADDPG) and RL algorithms
[7]		√	√	Deep reinforcement learning
[14]		√	√	Counterfactual multi-agent policy gradients (COMA) algorithm
[15]		√	√	Actor-critic neural networks (ACNN)
[16]		√	√	SEER representation
[19]		√	√	Augmented Lagrangian particle swarm optimization (ALPSO)
[20]		√	√	Automatic modular design approach (AutoMoDe)
[24]	Coordination	-	√	AudioLocNetv(deep learning module)
[31]		√	-	Not specified
[32]		√	-	End-to-end Neural Networks to train robots
[27]		√	-	Mean-field feedback control
[28]		√	-	Deep Neural Network (DNN) model
[29]		√	-	variant of the crawling probabilistic road map motion planning algorithm
[33]		√	-	distributed online reinforcement learning method
[34]		√	-	coordination algorithm
[51]	Optimization	-	√	PSO algorithm
[53]		-	√	streamlined algorithms
[36]		√	-	RetinaNet model, Salp Swarm Algorithm (SSA), Cascaded Long Short-Term Memory (CLSTM) model and Seeker Optimization Algorithm (SOA)

[37]		√	-	Distributing different layers of Convolutional Neural Networks (CNNs)
[47]		√	-	Decentralized deep reinforcement learning technology based on blockchain and Proximal Policy Optimization (PPO)
[48]		√	-	Adapted PSO
[38]		√	-	BSCAN, MIQCP and StringNet Herding
[39]		√	-	Dynamic wave expansion neural network (DWENN)
[43]		√	-	Boosted Trees (BST) and Bagged Trees (BT)
[45]		√	-	Genetic algorithm (GA)
[46]		√	-	Particle Swarm Optimization (PSO)
[49]		√	-	Robot Bean Optimization Algorithm (RBOA)
[50]		√	-	Automatic modular design method: AutoMoDe-Cedrata and AutoMoDe-Maple
[52]		√	-	PPO algorithm
[54]		√	-	Dijkstra algorithm
[55]		√	-	WC and WET algorithms
[44]		√	√	Decentralized ergodic planning
[35]	Optimization and Navigation	√	-	YOLOv8
[41]		√	-	Quantum-based path-planning algorithm and Grover's search algorithm
[42]		√	-	Genetic algorithms (GA) and Cellular automata techniques
[9]		√	-	Mean-Field Control (MFC), deep reinforcement learning (RL), and collision avoidance algorithms
[22]	Optimization and Coordination	√	-	Knowledge-Based Neural Ordinary Differential Equations (KNODE)
[23]		√	-	Surrogate models based on Gaussian processes (GPs), Artificial neural networks (ANNs) A hybrid evolutionary algorithm (HEA)
[40]		√	-	Genetic Algorithm (GA)
[30]		√	-	Not specified
[26]		√	-	Genetic Algorithm (GA)
[11]	Coordination and Navigation	√	-	ROS-NetSim
[25]		√	√	Neuro-evolutionary algorithm called Hill Climb Assembler Encoding
[56]	Fault Detection Optimization Coordination	√	√	evolutionary algorithm, Genetic Algorithm (GA) and Local Search algorithm (LS)

Overall, the findings of this systematic review offer valuable insights into the various applications of AI in swarm robotics and highlight the importance of continued research and innovation in this rapidly evolving field.

5. Conclusion and Future Work Directions

In conclusion, this systematic review has provided valuable insights into the current landscape of AI-driven approaches in swarm robotics. The study identified four key roles of AI in swarm robotics, including swarm navigation, coordination, optimization, and fault detection. These roles play a crucial role in enhancing the capabilities of robot swarms across various applications.

For future research, researchers should consider conducting real-world testing to enhance the applicability of AI-driven swarm robotics solutions. Furthermore, further exploration of AI algorithms and techniques tailored specifically for swarm robotics applications is needed. This includes developing more advanced fault detection and coordination strategies to improve swarm efficiency and adaptability. Additionally, future research should also focus on addressing the challenges and limitations identified in this systematic review, such as the lack of real-world testing and potential biases in participant feedback.

Overall, this systematic review provides a foundation for future research efforts in AI-driven swarm robotics, opening new opportunities for diverse applications.

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