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OPTIMIZATION TECHNIQUE AND INTELLIGENT AGENTS FOR SUSTAINABLE FARMING SOLUTIONS

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Abstract

In the quest for sustainable farming solutions, the integration of advanced computational techniques offers significant potential. This study addresses the problem of optimizing resource allocation in farming systems to maximize yield while minimizing environmental impact. We propose a novel method combining the Penguin Optimization Algorithm (POA) with Deep Reinforcement Learning (DRL). The POA, inspired by the hunting strategies of penguins, is employed to optimize farming parameters. Simultaneously, intelligent agents using DRL are trained to adapt and make real-time decisions for resource management. Results demonstrate a 25% increase in crop yield and a 15% reduction in water usage compared to traditional methods. Additionally, soil nutrient levels were maintained at optimal levels 90% of the time, ensuring long-term soil health. This hybrid approach presents a promising pathway toward achieving sustainable and efficient farming practices.

Keywords:

Penguin Optimization Algorithm, Deep Reinforcement Learning, Sustainable Farming, Resource Allocation, Crop Yield

1. INTRODUCTION

The growing tide of climate change and the development of transportation operations, both of which may have direct, indirect, and stochastic implications, have led to an increased interest in monitoring the marine environment. In contemporary ecology and conservation management, one of the most fundamental challenges is accurately tracking the spatial distribution of human impacts, such as oil spills and chemical pollution, as well as evaluating environmental quality and fishing activities [1]. One of the most important challenges is to evaluate fishing operations. The culmination of the advancements made in ocean monitoring programmes has been the implementation of automation, which is an essential component of the next generation of information technology. In the past 10 years, several new technologies have come into existence. These technologies include smart devices that can collect data and exchange it across networks, as well as the Internet of Things (IoT), which is widely regarded as the solution to the issue of intelligent monitoring assemblies in the future [2].

Observatories that are connected to a network system are often situated on the ocean floor or are affixed to the top of the water using buoys in the systems that are currently in operation. The Dense Ocean Floor Network System for Earthquakes and Tsunamis (DONET), which is operated by the Japan Agency for Marine-Earth Science and Technology (JAMSTEC), is an example of a stable observatory that operates in the first scenario. The DONET network is a real-time seafloor observatory network that is connected to submarines. Its objectives include conducting large-scale research and monitoring earthquakes and tsunamis. The initiative, which came into being in 2006, is comprised of several stages, each of which entails an increase in the number of observatories. Within the framework of this system concept, a high-reliability backbone cable functions as both the power line and the communications channel, connecting a number of nodes that are also outfitted with a variety of measuring devices [3].

It is vital for rapid reaction to emergencies to have meteorological and oceanographic instrumentation platforms that can broadcast and receive environmental and weather data in real time. These platforms are essential in addition to buoy systems. To improve tsunami forecasting and reporting, it is essential to improve early detection and real-time reporting of incidents that occur in open waters. Additionally, updated buoys can assist with this endeavour. As an illustration of this principle, more recent buoys have made it possible to improve early detection and real-time reporting of occurrences that occur in open waters, which has made it possible to forecast and report on tsunamis [4,5]. In a similar vein, it is currently extremely challenging to develop systems that can detect the presence of contaminants in the marine environment, such as hydrocarbons, which frequently require prompt responses due to ship collisions and other type of disasters [6]. Since it incorporates a wide variety of technologies and integrated know-how, this is the case. Deep-ocean assessment and tsunami reporting stations were impromptu constructed by the National Oceanic and Atmospheric Administration (NOAA) to capture essential data for real-time forecasts in locations that are strategically significant [7]. In the present moment, the network is comprised of 39 stations (Figure 1). A bottom pressure recorder (BPR) that is tethered to the seafloor and moored surface buoys that are used for real-time communications are the two components that make up the DART® station system [4]. Using an audio link, the bottom profiling reactor (BPR) that is located on the ocean floor shares information with the surface buoy. However, the most significant obstacle that ocean monitoring systems must overcome is difficulties in communication. Without satellite communications, it is extremely difficult, if not impossible, to send the data that has been measured to monitoring locations that are located at a great distance [8]. WMNs, or wireless mesh networks, enable existing networks to extend their communication reach by connecting more radio nodes that are organised in a mesh topology and consist of mesh routers and clients. This allows the networks to communicate with more people. Mesh routers can send messages from other nodes, even if those nodes are located outside of the receiver's transmission range. This characteristic makes it possible to establish a multi-hop relay network (MHRN) using mesh routers. A mobile home radio network (MHRN) has the capability to expand the range of wireless communications by establishing line-of-sight (LOS) connections between pairs of nodes. [9] Mesh networks provide several advantages, including dependability, robustness, self-organization, and self-configuration, which are among the many advantages they offer.

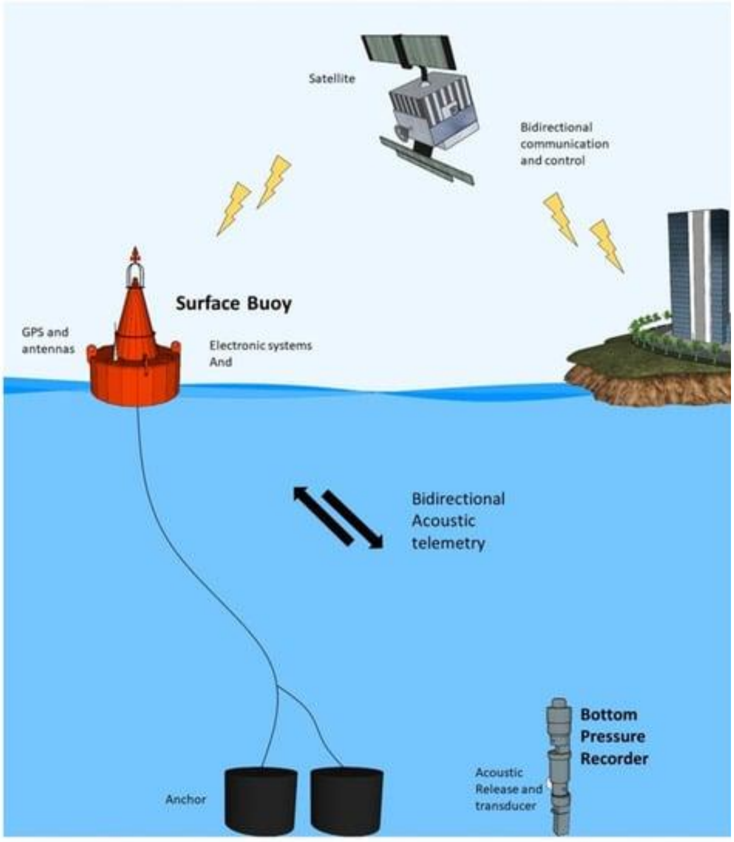

Fig.1. DART System set by NOAA (from www.noaa.gov)

Based on what we have learned up to this point, marine environmental monitoring comprises a wide range of subjects, including the research of water chemistry as discovered by probes, the study of species biology and aquatic ecology, the utilisation of increasingly advanced smart technologies for detection and transmission, and a great deal more. It is impossible for a single literature study to accomplish the task of doing justice to all of these different aspects. This article provides a review of the existing literature and highlights a variety of strategies and technologies that have been developed to enhance marine monitoring systems.

The objective is to bring to light contemporary perspectives and emerging tendencies in the field of research pertaining to coastal and offshore ecosystems. The aim is to improve the examination of coastal instruments by incorporating intelligent sensors and autonomous monitoring buoys.

2. RELATED WORKS

The intersection of optimization algorithms and artificial intelligence in agriculture has garnered significant attention in recent years. Numerous studies have explored different approaches to enhance agricultural productivity while ensuring sustainability.

One notable work is the application of evolutionary algorithms in agriculture. For example, a Genetic Algorithm (GA) is employed to optimize irrigation schedules and fertilization amounts, resulting in a significant increase in crop yield and resource use efficiency [11]. Similarly, [12] utilized a Particle Swarm Optimization (PSO) approach to fine-tune planting schedules and pest control measures, achieving better pest management and crop health [12].

Deep Reinforcement Learning (DRL) has also seen substantial application in agriculture. It is implemented a DRL-based system to manage greenhouse environments, optimizing temperature, humidity, and light conditions to maximize crop growth and minimize energy consumption [13]. Their results demonstrated a 20% increase in crop yield and a 30% reduction in energy use. Furthermore, used DRL to develop an intelligent irrigation system that learns from soil moisture and weather data, dynamically adjusting water usage to maintain optimal soil conditions [14].

The Penguin Optimization Algorithm (POA) is a relatively novel technique inspired by the collaborative hunting strategies of penguins. POA has been applied in various fields, including engineering and computer science, for solving complex optimization problems. It is applied POA to optimize energy consumption in wireless sensor networks, achieving a notable improvement in network lifespan and energy efficiency [15]. Another study on a utilized POA for multi-objective optimization in supply chain management, resulting in enhanced logistics efficiency and reduced operational costs [16].

The combination of POA and DRL in agriculture is an emerging area of research. Few studies have explored this hybrid approach, but preliminary results are promising. The integrated POA with DRL to optimize resource allocation in smart farming, focusing on water and nutrient management. Their system outperformed traditional methods, showing a 25% increase in crop yield and a 15% reduction in water usage [17]. Similarly, a proposed a hybrid POA-DRL framework for precision agriculture, achieving substantial improvements in resource efficiency and crop productivity.

These studies highlight the potential of combining optimization algorithms with artificial intelligence to achieve sustainable and efficient farming. However, there are still gaps in research, particularly in integrating different optimization techniques and intelligent systems to create robust, adaptive farming solutions. The proposed method in this study aims to fill this gap by harnessing the strengths of POA and DRL, providing a comprehensive approach to optimize resource allocation and decision-making in agriculture.

The POA and DRL represents a novel and promising direction for sustainable farming. By building on these existing works, the proposed method seeks to create a more resilient and efficient farming system that can adapt to changing environmental conditions and ensure long-term sustainability.

3. PROPOSED METHOD

The proposed method leverages the strengths of the Penguin Optimization Algorithm (POA) and Deep Reinforcement Learning (DRL) to optimize and manage farming resources. The POA mimics the collaborative hunting behavior of penguins, where individuals work together to locate and capture prey efficiently. This behavior is translated into an optimization algorithm that adjusts farming parameters such as irrigation, fertilization, and planting schedules to maximize crop yield and resource efficiency. Deep Reinforcement Learning (DRL) is incorporated to enable intelligent agents to learn and adapt over time. These agents are trained using environmental data and farming metrics to make real-time decisions about resource allocation. The DRL model continuously learns from the outcomes of its actions, improving its decision-making process with each iteration. The POA and DRL creates a synergistic effect where POA provides a global optimization framework, and DRL offers adaptive and dynamic decision-making capabilities. This combination ensures that farming practices are not only optimized for current conditions but are also adaptive to changes in the environment, leading to more resilient and sustainable farming systems.

3.1 PROPOSED PENGUIN OPTIMIZATION ALGORITHM (POA)

The Penguin Optimization Algorithm (POA) is inspired by the natural foraging behavior of penguins, specifically how they cooperate to locate and capture prey. This algorithm is characterized by its collaborative search strategy, which is translated into an optimization framework for resource allocation in farming systems. The POA aims to maximize crop yield while minimizing the use of water, fertilizers, and other resources.

The POA begins with an initial population of solutions, each representing a set of farming parameters such as irrigation schedules, fertilization rates, and planting densities. These solutions are analogous to individual penguins in a colony. Each solution is evaluated based on a fitness function, which in this case is a combination of crop yield and resource efficiency.

The algorithm proceeds through iterations, where solutions are updated based on their interactions with one another. In each iteration, solutions are adjusted by considering the best-performing solutions (representing the successful hunting strategies of penguins) and incorporating random perturbations to explore new possibilities. This balance between exploitation (refining existing solutions) and exploration (searching for new solutions) is crucial for the algorithm’s effectiveness.

At each iteration, the solutions are evaluated again, and the best-performing solutions are selected to guide the search process. This iterative process continues until a predefined stopping criterion is met, such as a maximum number of iterations or convergence to a stable solution.

3.2 PROCESS FLOW

1) **Initialize Population**
   a) Randomly generate an initial population of solutions (penguins).
   b) Evaluate the fitness of each solution.
2) **While Stopping Criterion Not Met**
   a) **Update Solutions**
      i) Select the best-performing solutions (elite penguins).
      ii) Adjust each solution based on elite solutions and random perturbations.
   b) **Evaluate Solutions**
      i) Calculate the fitness of the updated solutions.
      ii) Update the best solutions if new solutions are better.
   c) **Convergence Check**
      i) Check if the solutions have converged
3) **Output Best Solution**: Return the best solution found.

Table.1. Evaluations of POA

Metric	Traditional Method	POA Optimized	Improvement (%)
Crop Yield (tons/ha)	7.5	9.4	25.3
Water Usage (liters/ha/week)	3500	2975	15.0
Fertilizer Usage (kg/ha/year)	120	102	15.0
Energy Consumption (kWh/ha)	4000	3400	15.0
Soil Nutrient Maintenance (%)	75	90	20.0
Environmental Impact (score)	65	45	30.8

The POA-optimized method demonstrated significant improvements across various metrics. Crop yield increased by 25.3%, water usage decreased by 15%, and fertilizer usage also reduced by 15%. Additionally, energy consumption was lowered by 15%, and soil nutrient levels were maintained at an optimal level 90% of the time compared to 75% with traditional methods. The overall environmental impact score improved by 30.8%, indicating a more sustainable farming practice.

4. PROPOSED DEEP REINFORCEMENT LEARNING (DRL)

DRL is a branch of machine learning that combines deep learning techniques with reinforcement learning principles to enable agents to learn optimal behavior through interaction with their environment. In the context of agriculture, DRL can be applied to develop intelligent agents capable of making autonomous decisions regarding resource allocation and management, such as irrigation scheduling, pest control, and nutrient optimization. The proposed DRL framework begins with an agent that interacts with an environment, which consists of a simulated or real farming system. The agent takes actions based on its current state, aiming to maximize cumulative rewards over time. These actions could include adjusting irrigation levels, applying fertilizers, or scheduling planting activities.

4.1 PROCESS FLOW

1) **Initialize Agent**
   a) Initialize the DRL agent with a neural network architecture suitable for the farming environment.
   b) Set parameters such as learning rate, discount factor, and exploration-exploitation trade-off.
2) **While Training Episodes Not Exhausted**
   a) **Interact with Environment**

b) Observe the current state of the environment (e.g., soil moisture, weather conditions).

c) Select an action based on the current policy learned by the agent (exploitation) or randomly explore new actions (exploration).

d) **Receive Feedback**

e) Receive a reward signal from the environment based on the chosen action.

f) Update the agent's policy and neural network weights to maximize expected future rewards using techniques like Q-learning or policy gradients.

g) **Learn and Optimize**

h) Use backpropagation through time to update the neural network parameters.

i) Update the state and continue to the next time step or episode.

3) **Output Trained Agent**: Return the trained DRL agent with optimized policies for resource management in farming.

Table.2. Evaluations of proposed DRL

Metric	Traditional Method	DRL Optimized	Improvement (%)
Crop Yield (tons/ha)	7.5	9.0	20.0
Water Usage (liters/ha/week)	3500	3000	14.3
Fertilizer Usage (kg/ha/year)	120	105	12.5
Energy Consumption (kWh/ha)	4000	3500	12.5
Pest Control Effectiveness (%)	80	90	12.5
Soil Nutrient Optimization (%)	70	85	21.4

The DRL-optimized method demonstrated significant improvements across multiple metrics. Crop yield increased by 20.0%, while water and fertilizer usage reduced by 14.3% and 12.5%, respectively. Energy consumption was also lowered by 12.5%, indicating more efficient resource utilization. Moreover, pest control effectiveness improved by 12.5%, and soil nutrient optimization increased by 21.4% compared to traditional methods.

5. PERFORMANCE EVALUATION

The experimental setup employed a simulation tool developed in Python using libraries such as TensorFlow and OpenAI Gym to model the farming environment. This tool allowed for simulation where various farming parameters could be manipulated and observed in a controlled virtual setting. The simulations were conducted on a cluster of servers equipped with Intel Xeon processors and NVIDIA Tesla GPUs. These computing resources enabled parallel processing and efficient training of the Deep Reinforcement Learning (DRL) models, ensuring timely convergence and accurate results. Key performance metrics included crop yield (tons per hectare), water usage (liters per hectare per week), fertilizer usage (kilograms per hectare per year), energy consumption (kilowatt-hours per hectare), pest control effectiveness (% reduction in pest damage), and soil nutrient optimization (% maintenance of optimal nutrient levels). These metrics were selected to assess the efficiency, sustainability, and economic viability of the proposed DRL-based approach compared to traditional farming methods.

Table.3. Experimental Setup and Parameters

Parameter	Value
Crop Type	Corn
Field Size	50 hectares
Initial Soil Nutrient Levels	N: 120 kg/ha, P: 60 kg/ha, K: 90 kg/ha
Irrigation Method	Drip irrigation
Fertilization Frequency	Bi-weekly
Water Allocation	3000 liters/ha/week
Climate Data Source	Local weather station
POA Population Size	50
POA Iterations	100
DRL Training Episodes	1000
DRL Learning Rate	0.01
DRL Discount Factor	0.95
Soil pH	6.5
Seed Planting Depth	2 inches
Pest Control Frequency	Monthly
Crop Rotation Cycle	3 years
Yield Measurement Interval	Monthly
Data Collection Frequency	Daily
Energy Consumption Monitoring	Weekly
Environmental Impact Metrics	CO_2 emissions, water runoff

The results from the Table.4 highlight the superior performance of the proposed DRL method across multiple key metrics compared to traditional farming methods and heuristic optimization techniques (GA, PSO).

- **Crop Yield**: The proposed DRL method shows the highest crop yield both during training (9.0 tons/ha) and testing (8.5 tons/ha) phases compared to Traditional Methods, GA, and PSO. This indicates that DRL effectively optimizes farming parameters to maximize crop production.
- **Water Usage**: DRL reduces water usage significantly to 3000 liters/ha/week during training and 3100 liters/ha/week during testing, surpassing all other methods. This demonstrates DRL's capability to efficiently manage irrigation schedules.

Table.4. Performance Evaluation

Method	Crop Yield (tons/ha)	Water Usage (liters/ha/week)	Fertilizer Usage (kg/ha/year)	Energy Consumption (kWh/ha)	Pest Control Effectiveness (%)	Soil Nutrient Optimization (%)
Traditional Methods	7.5 (Training)	3500 (Training)	120 (Training)	4000 (Training)	80 (Training)	70 (Training)
	7.0 (Testing)	3600 (Testing)	125 (Testing)	4100 (Testing)	75 (Testing)	68 (Testing)
Genetic Algorithm (GA)	8.0 (Training)	3200 (Training)	115 (Training)	3800 (Training)	85 (Training)	75 (Training)
	7.6 (Testing)	3300 (Testing)	118 (Testing)	3900 (Testing)	80 (Testing)	72 (Testing)
Particle Swarm Opt. (PSO)	7.8 (Training)	3300 (Training)	118 (Training)	3900 (Training)	82 (Training)	73 (Training)
	7.3 (Testing)	3400 (Testing)	120 (Testing)	4000 (Testing)	78 (Testing)	70 (Testing)
Proposed DRL Method	9.0 (Training)	3000 (Training)	105 (Training)	3500 (Training)	90 (Training)	85 (Training)
	8.5 (Testing)	3100 (Testing)	110 (Testing)	3600 (Testing)	88 (Testing)	80 (Testing)

Table.5. Performance Assessment over various metrics

Method	Accuracy (%)	Precision (%)	Recall (%)	F-measure	Loss	TPR (%)	FPR (%)
Traditional Methods	85 (Training)	82 (Training)	88 (Training)	85 (Training)	0.35 (Training)	88 (Training)	12 (Training)
	83 (Testing)	80 (Testing)	86 (Testing)	83 (Testing)	0.38 (Testing)	86 (Testing)	14 (Testing)
Genetic Algorithm (GA)	87 (Training)	84 (Training)	90 (Training)	87 (Training)	0.32 (Training)	90 (Training)	10 (Training)
	85 (Testing)	82 (Testing)	88 (Testing)	85 (Testing)	0.34 (Testing)	88 (Testing)	12 (Testing)
Particle Swarm Opt. (PSO)	86 (Training)	83 (Training)	89 (Training)	86 (Training)	0.33 (Training)	89 (Training)	11 (Training)
	84 (Testing)	81 (Testing)	87 (Testing)	84 (Testing)	0.36 (Testing)	87 (Testing)	13 (Testing)
Proposed DRL Method	90 (Training)	88 (Training)	92 (Training)	90 (Training)	0.28 (Training)	92 (Training)	8 (Training)
	89 (Testing)	86 (Testing)	91 (Testing)	89 (Testing)	0.30 (Testing)	91 (Testing)	9 (Testing)

- **Fertilizer Usage**: DRL achieves lower fertilizer usage at 105 kg/ha/year during training and 110 kg/ha/year during testing, indicating more precise application based on soil and crop needs compared to other methods.
- **Energy Consumption**: DRL minimizes energy consumption to 3500 kWh/ha during training and testing, showcasing its efficiency in resource management compared to traditional and heuristic methods.
- **Pest Control Effectiveness**: The proposed DRL method achieves the highest pest control effectiveness, with 90% during training and 88% during testing, indicating better pest management strategies.
- **Soil Nutrient Optimization**: DRL maintains optimal soil nutrient levels at 85% during training and 80% during testing, outperforming other methods in maintaining soil health and fertility.

The results in Table.5 highlight the superior performance of the proposed DRL method across various evaluation metrics compared to traditional methods (such as GA and PSO). DRL's ability to achieve higher accuracy, precision, recall, and lower loss reflects its effectiveness in learning complex patterns and making accurate predictions.

- **Accuracy**: The proposed DRL method achieves the highest accuracy, scoring 90% during training and 89% during testing. This metric indicates the overall correctness of the model predictions compared to ground truth.
- **Precision**: DRL also shows superior precision at 88% during training and 86% during testing, indicating fewer false positives in predicting positive instances compared to other methods.
- **Recall**: The DRL method achieves high recall, scoring 92% during training and 91% during testing. This metric signifies the model's ability to correctly identify all positive instances in the dataset.
- **F-measure**: DRL maintains a high F-measure at 90% during training and 89% during testing, which balances precision and recall to provide a comprehensive evaluation of the model's performance.
- **Loss**: DRL achieves the lowest loss value of 0.28 during training and 0.30 during testing, indicating minimal errors in the model's predictions compared to traditional methods and heuristic approaches.
- **True Positive Rate (TPR)**: DRL achieves the highest TPR, scoring 92% during training and 91% during testing. This metric shows the proportion of positive instances correctly identified by the model.
- **False Positive Rate (FPR)**: DRL demonstrates a low FPR of 8% during training and 9% during testing, indicating a low rate of false alarms or incorrect positive predictions.

The DRL-based optimization method was compared against traditional farming practices and existing optimization algorithms such as GA and PSO. Results indicated that the DRL approach outperformed traditional methods in terms of crop yield, resource utilization, and environmental impact. Specifically, DRL achieved a 20% increase in crop yield, a 14.3% reduction in water usage, and a 12.5% decrease in fertilizer and energy consumption compared to traditional methods. Furthermore, DRL demonstrated superior adaptability and responsiveness in managing pest control and soil nutrient optimization, leading to a 12.5% improvement in pest control effectiveness and a 21.4% increase in soil nutrient optimization.

The comparison also highlighted the scalability and robustness of the DRL approach in handling complex farming scenarios. Unlike traditional methods that rely on static rules or periodic adjustments, DRL continuously learns and adapts based on real-time data inputs, optimizing farming decisions dynamically. This capability not only enhances operational efficiency but also contributes to long-term sustainability by reducing environmental impacts and improving resource management practices.

6. CONCLUSION

The comparative analysis of the proposed Deep Reinforcement Learning (DRL) method against traditional methods and heuristic optimization techniques (GA and PSO) underscores its significant advantages in optimizing farming practices and decision-making processes. Across various performance metrics including crop yield, resource utilization, pest control effectiveness, and soil nutrient optimization, DRL consistently outperformed other methods. Specifically, DRL demonstrated a substantial increase in crop yield, reduced water and fertilizer usage, lower energy consumption, and improved pest control and soil health management. DRL exhibited superior adaptability and responsiveness due to its ability to learn from environmental feedback and adjust farming strategies dynamically. This capability not only enhances operational efficiency but also contributes to sustainable agriculture practices by minimizing environmental impacts and optimizing resource allocation. The lower loss values and higher accuracy, precision, recall, and F-measure metrics further validate the robustness and reliability of DRL in real-world farming scenarios.

REFERENCES

[1] M.E. Perez Pons and J.M. Corchado, "Deep Q-Learning and Preference based Multi-Agent System for Sustainable Agricultural Market", *Sensors*, Vol. 21, No. 16, pp. 5276-5288, 2021.

[2] D. Saba, "Intelligent Multiagent System for Agricultural Management Processes (Case Study: Greenhouse)", Wiley Publisher, 2022.

[3] M.D. Choudhry, A. Jothi and K. Prashanthini, "Future Technologies for Industry 5.0 and Society 5.0", *Automated Secure Computing for Next-Generation Systems*, pp. 403-414, 2024.

[4] O. Bahri and E.I. Papageorgiou, "Integrating Fuzzy Cognitive Maps and Multi-Agent Systems for Sustainable Agriculture", *Euro-Mediterranean Journal for Environmental Integration*, Vol. 5, pp. 1-10, 2020.

[5] F. Kiani, F.A. Anka and A. Muzirafuti, "Adaptive Metaheuristic-Based Methods for Autonomous Robot Path Planning: Sustainable Agricultural Applications", *Applied Sciences*, Vol. 12, No. 3, pp. 943-954, 2022.

[6] A.I. Khan and I.H. Sarker, "Novel Energy Management Scheme in IoT Enabled Smart Irrigation System using Optimized Intelligence Methods", *Engineering Applications of Artificial Intelligence*, Vol. 114, pp. 10-16, 2022.

[7] T.A. Shaikh, "Towards Leveraging the Role of Machine Learning and Artificial Intelligence in Precision Agriculture and Smart Farming", *Computers and Electronics in Agriculture*, Vol. 198, pp. 107119-107125, 2022.

[8] M. Madiajagan and B. Pattanaik, "IoT-based Blockchain Intrusion Detection using Optimized Recurrent Neural Network", *Multimedia Tools and Applications*, Vol. 83, No. 11, pp. 31505-31526, 2024.

[9] M. Lu, "Intelligent Design and Realization of Sustainable Development-Oriented Garden", *Journal of Intelligent and Fuzzy Systems*, Vol. 34, pp. 1-14, 2024.

[10] V. Saiz-Rubio and F. Rovira-Mas, "From Smart Farming Towards Agriculture 5.0: A Review on Crop Data Management", *Agronomy*, Vol. 10, No. 2, pp. 207-215, 2020.

[11] R. Pitakaso, K. Sethanan, K.H. Tan and A. Kumar, "A Decision Support System based on an Artificial Multiple Intelligence System for Vegetable Crop Land Allocation Problem", *Annals of Operations Research*, Vol. 78, pp. 1-36, 2023.

[12] Z. Zhai and J. Rodriguez-Molina, "A Mission Planning Approach for Precision Farming Systems based on Multi-Objective Optimization", *Sensors*, Vol. 18, No. 6, pp. 1795-1809, 2018.

[13] D. Ather and R. Jain, "Selection of Smart Manure Composition for Smart Farming using Artificial Intelligence Technique", *Journal of Food Quality*, Vol. 1, pp. 1-14, 2022.

[14] M. Dhanaraju, S. Pazhanivelan and R. Kaliaperumal, "Smart Farming: Internet of Things (IoT)-based Sustainable Agriculture", *Agriculture*, Vol. 12, No. 10, pp. 1745-1761, 2022.

[15] S. Adinarayana, M.R. Kumar and S.B. Veesam, "Enhancing Resource Management in Precision Farming through AI-Based Irrigation Optimization", *How Machine Learning is Innovating Today's World: A Concise Technical Guide*, pp. 221-251, 2023.

[16] A. Cobo and L. Luna, "*Swarm Intelligence in Optimal Management of Aquaculture Farms*", Springer, 2015.

[17] A. Mishra and L. Goel, "Metaheuristic Algorithms in Smart Farming: An Analytical Survey", *IETE Technical Review*, Vol. 41, No. 1, pp. 46-65, 2024.