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RESEARCH ARTICLE

DRL-FLOOR CLEANING ROBOT USING DEEP REINFORCEMENT LEARNING ALGORITHM

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Abstract – Innovations in science and technology, particularly in the area of electronics, have had a significant impact on people's lives in today's rapidly evolving world. Robots are a well-known example of how technological advancements have enhanced and streamlined our way of life. Robots are designed to assist humans with their daily tasks in an effort to make work easier and more efficient. One such chore that people usually put off since it is tedious and exhausting is floor cleaning. The issue is that cleaning floors is a labor-intensive task because buildings have enormous floor spans. Brooms and mops are used in traditional cleaning methods, which have been demonstrated to be time-consuming. Furthermore, dust is unintentionally dispersed by these techniques. To overcome this problem a novel approach on cleaning robot Using Information of Things (IOT) based on Deep Reinforcement Learning algorithms (DRL) in introduced. The goal of the proposed work is to develop an inexpensive robot for floor cleaning. Deep Reinforcement Learning algorithm (DRL) was introduced for identifying and detecting the obstacles on the floor. The robot identifies the obstacles on the floor by using sensors. Various sensors are deployed for identifying obstacles on the floor like ultrasonic sensor, LIDAR sensor on floor cleaning robot. The sensor is used to identify, collect and deposit the trash and accelerometer. Deep reinforcement learning is combined with deep learning algorithm for training the floor cleaning robot. The proposed work DRL achieves about 2.04% and 3.06% than MCDM and SWCVAE algorithms in accuracy.

Keywords *– Internet of Things, Deep Reinforcement algorithm, ultra sonic sensor, LIDAR sensor.*

1. INTRODUCTION

In the quickly changing world of today, advancements in science and technology, especially in the field of electronics, have had a profound impact on people's lives [1]. The creation of robots is one prominent illustration of how these developments have improved and simplified our way of life [2]. Robots are made to help people with their everyday jobs in an effort to make work easier and more efficient because effective task completion is becoming more and more important. In closed spaces like residences, community centers, shopping malls, hospitals, etc., cleaning and disinfection are crucial measures in halting the spread of infectious diseases [3]. Floor cleaning is one such activity that is frequently put off since it is tiresome and boring [4]. Numerous cleaning robots have been proposed, including ones made for cleaning solar panels, floors, windows, stairs, drains, pavement, pools, and medical equipment. The problem is that buildings have large floor expanses, which makes floor cleaning a labor-intensive task [5].

Traditional cleaning techniques, which involve brooms and mops, have been shown to be time-consuming and frequently cause users to become uncomfortable and exhausted [6]. Additionally, these Techniques inadvertently spread dust, which can aggravate respiratory and flu-related conditions. A floor-cleaning robot has been proposed as a potentially creative solution to this problem [7]. Because of its capacity to revolutionize floor cleaning in a variety of settings, including homes, hotels, flats, and business venues, robotic cleaners have attracted a lot of interest in robotics research [8]. The creation of sophisticated floor-cleaning robots has proven essential to overcoming these obstacles. To overcome this problem a novel approach on cleaning robot Using IOT based on Deep Reinforcement Learning algorithms (DRL) in introduced. The main goal of this research is to develop an inexpensive cleaning robot that will meet the needs of users in the lower and middle classes.

In this paper, a novel floor cleaning robot using IOT based on Deep Reinforcement Learning algorithm (DRL) is introduced. The floor cleaning robot is deployed with ultrasonic sensor and LIDAR sensor for identifying the obstacles on the floor. After that, the reward system is educated by deep Reinforcement algorithm using sensors placed within it through trial and error.

The main contribution of the research is:

- A novel floor cleaning robot using IOT based on Deep Reinforcement Learning algorithm (DRL) was introduced for identifying and detecting the obstacles on the

floor. The robot identifies the obstacles on the floor by using sensors.
- Various sensors are deployed for identifying obstacles on the floor like ultrasonic sensor, LIDAR sensor on floor cleaning robot. The sensor is used to identify, collect and deposit the trash and accelerometer.
- Deep reinforcement learning is combined with deep learning algorithm for training the floor cleaning robot.
- The developed DRL has been carried out by evaluation metrics such as accuracy and energy consumption.

The sections that follow are arranged as follows: section 2 represents the literature review, section 3 represent the proposed methodology, section 4 represent the results and discussion, section 5 represent the conclusion.

2. LITERATURE REVIEW

To determine Floor cleaning using IoT for efficient and time-consuming process in real-time. Trash collection, energy consumption, area coverage, anomaly detection etc. A brief comprehensive study has been carried out from this research survey.

In 2020, M. N. Mohammed et.al [9], has proposed a feasible and efficient garbage collection system design for cleaning up debris from rivers, channels, and lakes. The trash collection system is specifically designed to be used for removing a variety of material, such as tires that have been disposed of, logs, trash, and gliding litter. Utilizing IoT technology, which can monitor and manage the entire process, is part of the integrated system. Since the suggested design has the ability to replace manual labor processes, directing to pick up a wide variety of flotsam and jetsam with good quality by lowering time taken.

In 2020, M. A. Viraj j Muthugala et.al [10], has introduced a new technique to calculate the trade-off between energy consumption and area coverage of a self-reconfigurable floor cleaning robot based on tiling theory based on user preference. The suggested system's behavior has been assessed using a variety of test cases. The suggested idea can take into consideration the robot's current state while adjusting the trade-off between area coverage and energy consumption according to user preferences.

In 2020, Tingting chen et.al [11], has introduced an industrial robot anomaly detection system that operates without supervision, the sliding-window convolutional variational autoencoder (SWCVAE). The ability to handle multivariate time series data allows for the spatial and temporal realization of real-time anomaly detection. Using a KUKA KR6R 900SIXX industrial robot, this technique has been validated, and the outcomes demonstrate that the suggested model can effectively identify anomalies in the robot. Therefore, future study will focus on figuring out how to enhance the model's performance in online learning.

In 2020, Xu miao et.al [12], has developed a cleaning distribution strategy based on map decomposition for coverage path planning in order to minimize the cleaning time of multi-cleaning robots. Additionally, the suggested cleaning distribution approach was used to resolve the issue of robot collisions during the cleaning process. The method divides the multi-cleaning robots into Rm and Rs, where Rm used the suggested map decomposition method to break down the full map into several sub-maps. In order to further reduce the cleaning time for larger environments, we also intend to enhance the algorithm.

In 2021, Madan mohan rayguru.et.al [13], has developed a novel saturated output feedback controller, for reconfigurable pavement sweeping wheeled mobile robots. EHOs were used to predict the dynamic uncertainties resulting from external disturbances and reconfiguration, However, to deal with actuator saturation, an approximate dynamic inversion controller was developed. The effectiveness of the suggested method over the state of the art is confirmed by the experimental results using a PANTHERA self-reconfigurable robot.

In 2021, Tao Jin et.al [14], has introduced a vacuum-controlled soft pneumatic actuator to achieve the compound motion of contraction and twist. When two actuators with reverse creases are combined, it provides pure contraction and the twist direction changes as the crease angle changes. The actuator has a response time of less than 0.3 seconds, can lift 180 times its own weight, and achieves a contraction ratio of 47%. In future, accuracy can be enhanced by employing deep learning algorithms.

In 2020, Jaeseok Kim et.al [15], has proposed a trained robot to use a learning from demonstration paradigm to carry out two distinct cleaning chores over a table. CNN are employed to make cleaning movements in accordance with the demos and generalize them to different. When compared to the case where no data augmentation was utilized, the employment of methods has decreased the requirement for a large training set; just 20% of the recorded data was required to attain a similar test error.

This section provides a summary of the main ideas in the research as well as the crucial and relevant elements that provide the basis for assessing the purpose and extent of the study.

According to research in the literature, The performance metrics, Battery life and limited cleaning performance. The proposed technique has been suggested as a solution to these problems.

3. PROPOSED METHOD

A novel floor cleaning robot using IOT based Deep Reinforcement learning algorithm (DRL) was introduced for identifying and detecting the obstacles on the floor. The robot identifies the obstacles on the floor by using sensors. Various sensors are deployed for identifying obstacles on the floor like ultrasonic sensor, LIDAR sensor on floor cleaning robot. The sensor is used to identify, collect and deposit the trash and accelerometer. Deep reinforcement learning is combined with deep learning algorithm for training the floor cleaning robot. Figure 1 represents a block diagram of proposed DRL and Figure 2 represents the hardware of proposed DRL module.

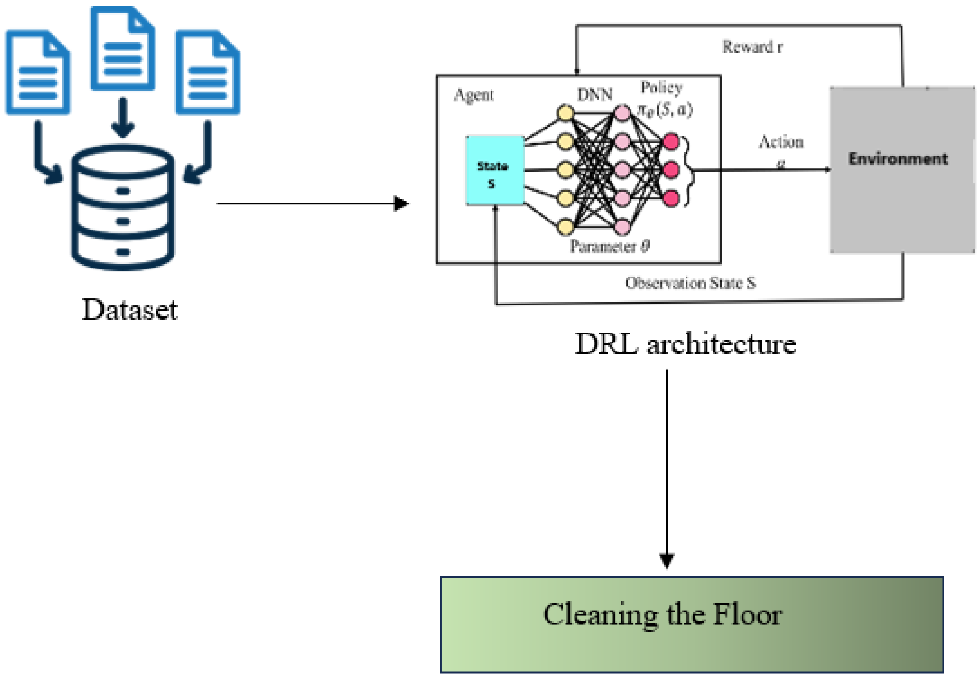


Figure 1. Block diagram of Proposed DRL

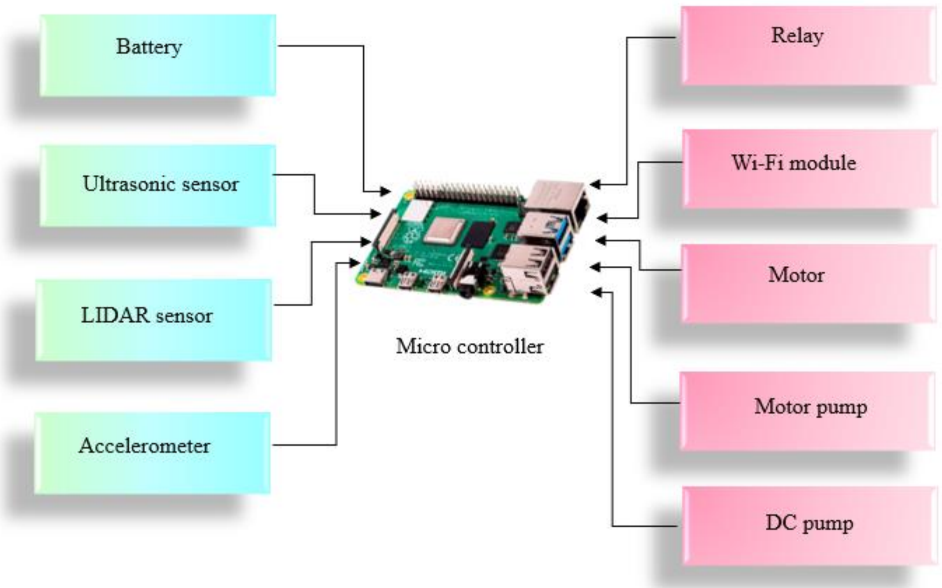


Figure 2. Hardware of proposed DRL module

3.1 Hardware components

The block diagram consists of battery of 12v, micro controller node MCU, Relay of 12v, Dc pump 0f 6v to 12v and DC motor of 12v, ultra sonic sensor and mopping brush. The relay receives the electrical supply. When the relay gets a signal from a sensor, it functions as a switch to regulate the water pump. The mop is moved by a DC motor to clean the floor, and it can also revolve in a 360-degree circle. Here, the floor is being mopped in order to guide the DC motors' forward and backward movements. It works automatically by detecting the obstacles on the floor.

3.1a Ultrasonic sensor

Figure 3. Ultrasonic sensor

To detect or measure the distance between two objects, ultrasonic sensors use ultrasonic sound waves. To ascertain the object's proximity, an ultrasonic sensor sends and receives ultrasonic pulses from the transducer. They are used in industrial operations and robotic obstacle detection systems. Figure 3 represents an ultrasonic sensor.

3.1b Dc Motor

The control circuitry and the motors are communicated with by the motor drivers. The motor requires a high current even if the controller circuit utilizes low current signals. An electronic gadget known as a motor facilitates the transformation of electrical energy into mechanical energy. As a result, a motor driver allows you to use electricity to perform automatic operations. Figure 4 represents a motor device.

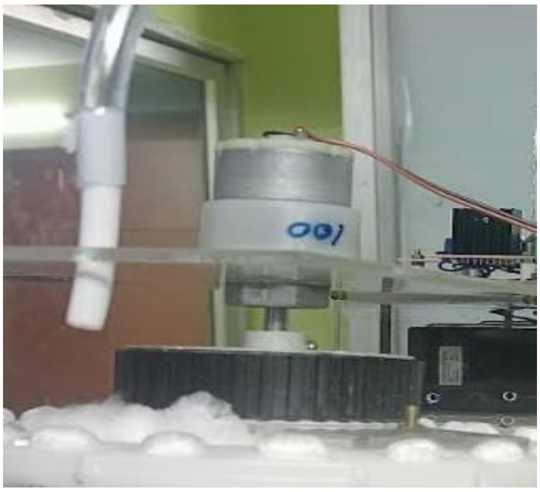


Figure 4. DC Motor

3.1c Battery

The most popular and portable 12V battery is the Hi-Watt 9V battery. It is an inexpensive, high-capacity, non-rechargeable solution for a variety of electrical gadgets. Like regular AA and AAA batteries, it is based on the chemistry of zinc carbon and is readily replaceable if it is drained.

Figure 5. battery

3.1d Microcontroller

Figure 6. Micro controller

A microcontroller unit (MCU) is a tiny integrated circuit computer. Microprocessors are computer processors that include all of the logic and control for processing data on one integrated circuit (IC) or a small number of ICs. The IC can conduct arithmetic operations and read and carry out software instructions. Combinational and sequential digital logic are both included in microprocessors, which work with binary number system-represented numbers and symbols

3.1e Mopping Brush

Figure 7. Mopping brush

Utilizing IoT technology for mopping devices, the primary function of mopping brush is to offer general cleaning coverage by agitating and sweeping debris off corners and edges. Mopping brushes make it easier to wipe the water on the floor and move it into the device's center of travel. With its rotational motion, the dirt and water are dislodged to a large extent, so that they can be easily cleaned and remove from the cleaning process. Figure 7 represents image of mopping brush.

3.1f Water Tank

Figure 8. Water Tank

There are two components to the mopping system's water tank. The water pump receives water from the first one, and the mop cloth that is attached to it receives water from the second one. Figure 8 represents of water Tank.

3.2 Reward Function

To generate incentive signals for training neural networks, the immediate reward qs function's description is provided. Termination states, however, must also get compensation. As a result, the neural network training reward function is as follows:

$$q(a_s, b_s) = \begin{cases} q_{f \ if \ \delta_s < \eta_\delta} \\ q_a \ \ if \ l_{min,q} < \eta_l \\ q_s \quad otherwise, \end{cases} \quad (1)$$

where the distance threshold to the goal, at which it is deemed reached, is represented by ηδ. A collision is deemed to have happened when ηl, the distance threshold to the nearest obstacle, is reached.

3.3 Knowledge collection

The floor cleaning robot use sensor for identifying the obstacles on the floor by utilizing the sensor. In this paper, ultrasonic and load sensor is deployed for sensing the obstacles and trash on the floor. The HC-SR04 ultrasonic sensor has been used for two system functions. This sensor's primary function is to determine how far away a target object is from it. One of these sensors serves as a full-level sensor in this application, and the other one has been employed as an ambient distance detector.

Accordingly, the mathematical analysis is displayed here. The j th rule's firing strength, αj, is calculated as follows:

$$\alpha_j = \mu Q_j(Q) \wedge \mu B_j(B) \quad (2)$$

The mopping tool's front side is equipped with an ultrasonic sensor. It determines whether there is trash close to the floor cleaning equipment, and if so, the mop gathers it. Accelerometers can detect when an object changes speed, direction, or moves from a stationary to a moving state.

3.4 Deep Reinforcement Learning (DRL)

DRL is a useful method for handling a large-scale action space and state space. The DRL algorithm's ultimate objective is to identify the best course of action $\pi^*$to maximize the expected return, also known as the long-term cumulative reward and represented by the state value function D. The agent's ongoing interactions with the unknowable environment led to a series of decisions. The value function F under a policy π at scheduling time step n can be expressed as

$$D_\pi = F_\pi[H^a] = F_\pi[S^a + \gamma S^{a+1} + \gamma^2 S^{a+1} + \cdots] \quad (3)$$

As a discounted factor, γ ∈ [0, 1], demonstrating the significance of the benefits in the future for the total return, S represents the immediate reward earned at each timestep and the expectancy operator is F [·].

The agent acts in each contact according to the states C^a that are seen. after which the environment gives it a new state and a feedback reward (S). The K-function is the action-state value function of a state-action pair.

$$K_\pi(c, b; \theta) = F_\pi[N^t | c^a = c, b^a = b]$$

$$= F_\pi[\sum_{l=a}^{\infty} \gamma^{l-a} S^l | c^a = c, b^a = b] \quad (4)$$

where the DNN parameter is θ. The ideal value is then obtained.

$$D_*(c) = \max_\pi D_\pi(c), K_*(c, b) = \max_\pi K_\pi(c, b) \quad (5)$$

and the best course of action:

$$\pi_* = arg \max_\pi D_\pi(c), \pi_* = \text{argmax}_\pi K_\pi(c, b) \quad (6)$$

Finding the best behavior plan for the agent to achieve the best rewards is the aim of the DRL. The value-based approach and the policy-based approach are the two ways to arrive at the best policy. The value-based approaches choose an action with the highest value after learning the K function. As an alternative, the policy gradient approaches focus on explicitly modeling and optimizing the policy $\pi_\theta(b|c)$ using a parameterized function with respect to θ. The action is selected in the policy gradient based on $\pi_\theta(b|c)$ .It uses the softmax function to distribute action probabilities.

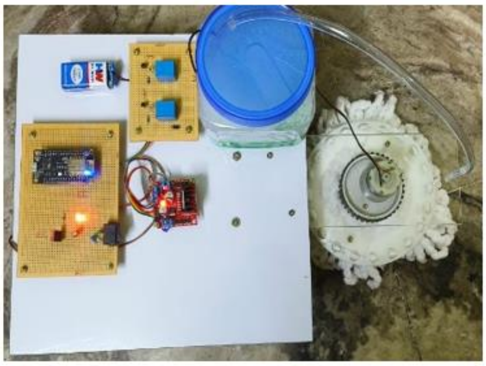
$$\pi_\theta(b|c) = \frac{e^{\emptyset(c,b)^T}\theta}{\sum_{p=1}^{p} e^{\phi(c,b_l)^T}\theta'} \quad (7)$$

where φ (c, b) is the feature vector

4. RESULTS AND DISCUSSIONS

Deep Reinforcement Learning algorithm (DRL) was introduced for identifying and detecting the obstacles on the floor. The robot identifies the obstacles on the floor by using sensors. Various sensors are deployed for identifying obstacles on the floor like ultrasonic sensor on floor cleaning robot. Python-based Deep Reinforcement learning method that use to train the module. Comparison on energy consumption and accuracy were made between the proposed DRL technique and Existing techniques. The proposed work DRL achieve about 39.8% and 16.5% than MCDM and SWCVAE algorithms in energy consumption and also DRL achieves about 2.04% and 3.06% than MCDM and SWCVAE algorithms in accuracy.

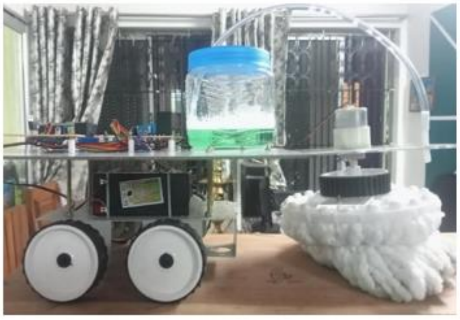
"Design and Implementation of Floor Cleaning Robot" paradigm that has been proposed. Figure 9(a),9(b), 9(c) and 9(d) shown a representation of proposed DRL. In a shorter amount of time, the floor cleaning robot produces the greatest cleaning results. The robot moved at an average speed of 0.60 m2 per second. In 13 minutes, the suggested method can clean a 3.048 m x 3.048 m space. The robot can operate with minimal faults due to the limits of the ultrasonic, but these are insignificant and pleasant.



(a)

(b)

(c)



(d)

Figure 9. Design and Implementation of proposed DRL model

Figure 10 represents an energy consumption of proposed DRL technique with the existing technique. Which is sophisticated with MCDM and SWCVAE. The proposed work DRL achieve about 39.8% and 16.5% than MCDM and SWCVAE algorithms in energy consumption.

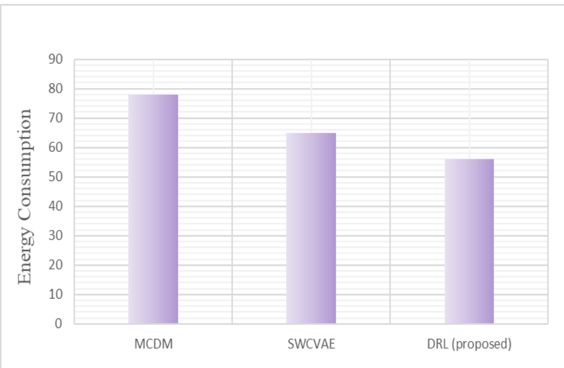


Figure 10. Energy consumption

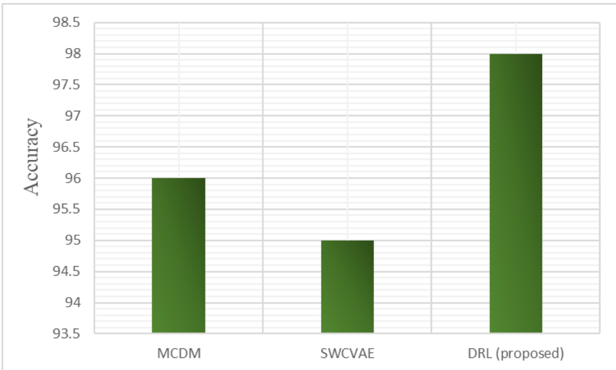


Figure 11. Accuracy of proposed DRL module

Figure 11 represents an accuracy of proposed DRL technique with the existing technique. Which is sophisticated with MCDM and SWCVAE.The proposed work DRL achieves about 2.04% and 3.06% than MCDM and SWCVAE algorithms in accuracy.

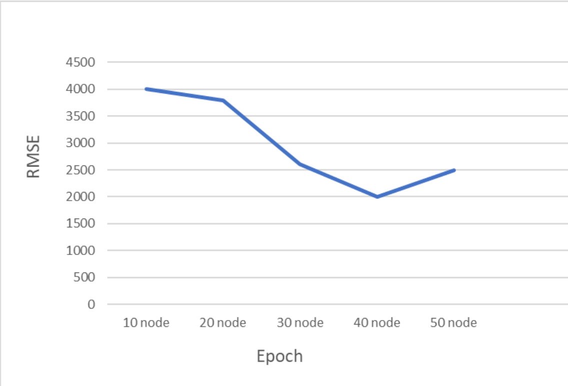


Figure 12. RSME comparison epoch of proposed DRL module

Figure 12 represents the Root mean square error (RMSE) comparison epoch of proposed DRL module. Across 10-50 nodes of epoch the RMSE value varies from 0 - 4500. The proposed DRL has low RMSE at node 40 than node 10 which has 4000 RMSE accurate prediction

5. CONCLUSION

In this paper, A novel floor cleaning robot using IOT based on Deep Reinforcement Learning algorithm (DRL) was introduced for identifying and detecting the obstacles on the floor. The robot identifies the obstacles on the floor by using sensors. Various sensors are deployed for identifying obstacles on the floor like ultrasonic sensor, LIDAR sensor on floor cleaning robot. The sensor is used to identify, collect and deposit the trash and accelerometer. Deep reinforcement learning is combined with deep learning algorithm for training the floor cleaning robot. The goal of the proposed work is to develop an inexpensive robot for floor cleaning. Performance evaluation of the suggested strategy is done using the python simulator. The result shows, the proposed work achieves about 2.04% and 3.06% than MCDM and SWCVAE algorithms in accuracy and achieves better energy consumption than the existing techniques. In future work, solar panel can be implemented and energy consumption can be reduced.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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REFERENCES

[1] B. Ramalingam, J. Yin, M. Rajesh Elara, Y.K. Tamilselvam, M. Mohan Rayguru, M.V.J. Muthugala, and B. Félix Gómez, "A human support robot for the cleaning and maintenance of door handles using a deep-learning framework", *Sensors*, vol. 20, no. 12, pp. 3543, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] A.H. Kassim, M.Y.M. Zain, M.A.T.M. Yusoh, M.N. Sidek, R.M.N.R. Daud, A.I.M. Arifin, and M.F.M. Zin, "Internet of things-based floor cleaning robot", *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 32, no. 3, pp. 1353-1360, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] R. Cimurs, and E.A. Merchán-Cruz, "Leveraging Expert Demonstration Features for Deep Reinforcement Learning in Floor Cleaning Robot Navigation", *Sensors*, vol. 22, no. 20, pp. 7750, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] J. John, M.S. Varkey, R.S. Podder, N. Sensarma, M. Selvi, S.V.N. Santhosh Kumar, and A. Kannan, "Smart prediction and monitoring of waste disposal system using IoT and cloud for IoT based smart cities", *Wireless Personal Communications*, vol. 122, no. 1, pp. 243-275, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[5] D. Ashok, M. Pavithra, T. Periyanayaki, and C. Midhuna, "revolutionizing floor cleaning: design and development of a smart solar-powered floor cleaning machine," 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] K. ManiRaj, K. Dasari, B. Ravi, P. Madamanchi, M. Lanka, and B. Kumar, "Design of automated solar floor cleaner using iot", *In 2022 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC),* pp. 1-5, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] K. Sathish, A. Dhanke, R. Mohandas, A.M. Gund, R. Kiruthiga, and J. Ranga, "Robust Design of Floor Cleaning Robot with Smart Power Handling Abilities Based on Solar Assisted Renewable Energy Sources", *In 2024 5th International Conference on Electronics and Sustainable Communication Systems (ICESC)*, pp. 239-246, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[8] M.S. Shaikh, K. Bhushanwar, N. Khodifad, and S.I. Ali, "Dual Purpose IoT Enabled Smart Cleaner Hexabot with Edge Detection Mechanism," *In 2024 International Conference on Advances in Computing Research on Science Engineering and Technology (ACROSET)*, pp. 1-6, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] M.N. Mohammed, S. Al-Zubaidi, S.H.K. Bahrain, M. Zaenudin, and M.I. Abdullah, "Design and development of river cleaning robot using IoT technology", *In 2020 16th IEEE International Colloquium on Signal Processing & Its Applications (CSPA),* pp. 84-87, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[10] M.V.J. Muthugala, S.B.P. Samarakoon, and M.R. Elara. "Tradeoff between area coverage and energy usage of a self-reconfigurable floor cleaning robot based on user preference", *IEEE Access*, vol. 8, pp. 76267-76275, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[11] T. Chen, X. Liu, B. Xia, W. Wang, and Y. Lai, "Unsupervised anomaly detection of industrial robots using sliding-window convolutional variational autoencoder", *IEEE Access*, vol. 8, pp. 47072-47081, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[12] X. Miao, H.S. Lee, and B.Y. Kang, "Multi-cleaning robots using cleaning distribution method based on map decomposition in large environments", *IEEE Access*, vol. 8, pp. 97873-97889, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[13] M.M. Rayguru, R.E. Mohan, R. Parween, L. Yi, A.V. Le, and S. Roy, "Output feedback based robust saturated controller design for pavement sweeping self-reconfigurable robot", *IEEE/ASME Transactions on Mechatronics*, vol. 26, no. 3, pp.1236-1247, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[14] T. Jin, L. Li, T. Wang, G. Wang, J. Cai, Y. Tian and Q. Zhang, "Origami-inspired soft actuators for stimulus perception and crawling robot applications", *IEEE Transactions on Robotics*, vol. 38, no. 2, pp. 748-764, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[15] J. Kim, N. Cauli, P. Vicente, B. Damas, A. Bernardino, J. Santos-Victor, and F. Cavallo, Cleaning tasks knowledge transfer between heterogeneous robots: A deep learning approach. Journal of Intelligent & Robotic Systems, vol. 98, pp. 191-205, 2020. [CrossRef] [Google Scholar] [Publisher Link]

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