KOMPUTASI: JURNAL ILMIAH ILMU KOMPUTER DAN MATEMATIKA
VOL. 23 (2) (2026), XX-XXp-ISSN: 693-7554, e-ISSN:2654-3990

Solar Panel Energy Analysis on Remote Control Mobile Robots

Syarif Hidayatulloh[1], **Teguh Puja Negara**[2], **Agus Ismangil**[3*], **Syaeful Anwar**[4*]

[1,2,3] Department of Computer Science, Faculty of Mathematics and Natural Science, Pakuan University, Bogor, West Java, 16143, Indonesia.

[4] Student Study Program Computer Science, Faculty of Mathematics and Natural Science, Pakuan University Bogor, West Java, 16143, Indonesia

Abstract

The growing deployment of remotely controlled mobile robots in surveillance, environmental monitoring, and disaster response requires reliable and energy-efficient power systems to ensure extended operational capability. Conventional battery-powered robots are constrained by limited operating time, making renewable energy integration an attractive alternative. This study investigates the energy performance of a 50 Wp photovoltaic (PV) panel integrated into a remotely controlled mobile robot and evaluates its effectiveness in extending the robot's operational endurance. The experimental platform consists of a 50 Wp monocrystalline solar panel, a 12 V lithium battery, a solar charge controller with maximum power point tracking (MPPT), and a mobile robot equipped with voltage, current, and power monitoring sensors. Performance evaluations were conducted under solar irradiance levels ranging from 350 to 980 W/m². Experimental results show that the PV system achieved a maximum output power of 46.8 W, corresponding to a peak conversion efficiency of 18.6% under optimum sunlight conditions. The maximum charging current reached 3.72 A, reducing the battery charging time by 41.3% compared with conventional charging. During continuous outdoor operation, the robot exhibited an average power consumption of 22.5 W. The integration of the 50 Wp PV panel extended the robot's operating time from 4.6 hours to 6.5 hours, representing an improvement of 41.3%, while reducing battery energy consumption by 33.8%. These findings demonstrate that integrating a 50 Wp photovoltaic system significantly enhances the energy efficiency, operational endurance, and sustainability of remotely controlled mobile robots, making it a promising solution for long-duration outdoor missions.

Keywords: *Photovoltaic panel, 50 Wp solar panel, mobile robot, remote control, renewable energy, energy efficiency, photovoltaic system.*

1. Introduction

The rapid advancement of mobile robotics has significantly transformed numerous sectors, including environmental monitoring, industrial inspection, agricultural automation, surveillance, disaster response, and military reconnaissance [1]. Remotely controlled mobile robots have become an effective solution for performing tasks in hazardous or inaccessible environments while minimizing human exposure to risk. These robotic systems are typically equipped with electric motors, embedded controllers, wireless communication modules, cameras, and multiple sensors that require a continuous and reliable power supply [2]. Consequently, the operational performance of a mobile robot is highly dependent on the availability and efficiency of its onboard energy system. Despite remarkable progress in robotic technologies, energy limitation remains one of the most critical challenges in the deployment of mobile robots. Most commercially available mobile robots rely exclusively on rechargeable batteries as their primary energy source [3]. Although modern lithium-based batteries offer high energy density, their finite capacity restricts

*Corresponding author. *E-mail address: a.ismangil.physics@gmail.com*
Received: 02 March 2026, Accepted: 30 July 2026 and available online 31 July 2026
DOI: https://doi.org/10.33751/komputasi.v23i2.99

operational duration, particularly during continuous outdoor missions involving high-power components such as drive motors, wireless communication devices, and real-time vision systems[4]. Frequent battery replacement or recharging interrupts mission continuity, increases operational costs, and limits the practical deployment of robots in remote areas where electrical infrastructure is unavailable.

The increasing global demand for sustainable energy has encouraged researchers to integrate renewable energy technologies into autonomous and remotely operated robotic systems. Among various renewable energy sources, solar photovoltaic (PV) technology has emerged as one of the most promising alternatives because of its clean energy production, low maintenance requirements, long operational lifetime, and decreasing installation cost. Photovoltaic systems directly convert solar radiation into electrical energy that can either power electronic devices or recharge onboard batteries [5]. Integrating photovoltaic panels into mobile robots offers the potential to reduce battery dependency while extending mission duration without requiring additional external charging infrastructure. Indonesia possesses substantial solar energy resources due to its geographical location within the tropical region. The country receives an average daily solar irradiation of approximately 4.8–5.5 kWh/m²/day throughout most of the year, making photovoltaic technology particularly attractive for outdoor robotic applications. This abundant solar potential provides opportunities for developing sustainable robotic platforms capable of operating for extended periods under natural environmental conditions [6]. Consequently, integrating photovoltaic energy harvesting into mobile robots represents an important research direction for supporting future intelligent transportation systems, precision agriculture, environmental monitoring, and autonomous surveillance [7].

Previous studies have investigated solar-powered mobile robots from various perspectives. Several researchers focused on mechanical design optimization and lightweight chassis development to improve energy efficiency. Others investigated autonomous navigation algorithms, wireless communication systems, obstacle avoidance techniques, or intelligent path planning while utilizing solar energy as an auxiliary power source. Research has also been conducted on photovoltaic maximum power point tracking (MPPT) techniques to maximize energy harvesting under varying irradiance conditions. Furthermore, numerous studies evaluated photovoltaic module efficiency, battery charging characteristics, and energy management strategies in standalone renewable energy systems.

Although these studies have contributed significantly to the advancement of solar-powered robotic technologies, several limitations remain. First, many existing studies emphasize robot navigation and control performance while providing limited quantitative analysis of photovoltaic energy contribution during actual robot operation. Second, most investigations evaluate photovoltaic performance independently from the robot's dynamic energy consumption, making it difficult to determine the real impact of solar energy integration on operational endurance [7]. Third, relatively few studies present comprehensive experimental measurements involving solar irradiance, photovoltaic output power, battery charging characteristics, robot power consumption, and mission duration within a single integrated framework. Consequently, the relationship between photovoltaic energy generation and robot operational performance remains insufficiently understood, particularly for remotely controlled mobile robots intended for outdoor applications.

Another important limitation concerns the photovoltaic capacity used in previous research. Many prototype robots employ relatively small solar modules (typically below 20 Wp), which are often incapable of supplying sufficient power to compensate for continuous energy consumption during robot movement [8]. Consequently, the actual benefit of photovoltaic integration becomes marginal under practical operating conditions. The application of a 50 Wp monocrystalline photovoltaic panel provides significantly greater energy harvesting capability while maintaining acceptable dimensions and weight for medium-sized mobile robotic platforms. However, quantitative evaluation of its effectiveness under varying environmental conditions has received limited attention in the literature.

To address these research gaps, this study investigates the energy performance of a remotely controlled mobile robot equipped with a lithium battery energy storage system and an MPPT solar charge controller [9], [10]. The proposed system continuously monitors solar irradiance, photovoltaic voltage, charging current, output power, battery voltage, and robot energy consumption during outdoor operation. Performance evaluation is conducted under different solar irradiation conditions to determine the capability of the photovoltaic system to support robot operation and improve overall energy efficiency [11], [12], [13]. Unlike previous studies that primarily concentrate on photovoltaic efficiency or robotic control independently, this research performs a comprehensive energy analysis by integrating photovoltaic generation characteristics with the actual electrical load profile of the robot. The study quantitatively evaluates the contribution of solar energy to battery charging performance, energy utilization, and operational endurance through real-time experimental measurements. Such analysis provides a more realistic understanding of photovoltaic-assisted robotic systems operating under practical environmental conditions.

2. Methods

This study employed an experimental research approach to evaluate the energy performance of a photovoltaic-powered remotely controlled mobile robot. The experimental procedure consisted of designing the electrical power system, integrating the photovoltaic module with the robot platform, measuring electrical parameters during operation, and analyzing the harvested solar energy under different solar irradiance conditions [14], [15], [16].

The proposed system utilizes a 50 W monocrystalline photovoltaic panel as the primary renewable energy source. Electrical energy generated by the photovoltaic module is regulated through a Maximum Power Point Tracking (MPPT) solar charge controller before charging the lithium battery [17],[17], [18]. The battery supplies electrical power to the mobile robot through a DC-DC voltage regulator, ensuring stable voltage for the controller, sensors, communication modules, and drive motors [19].

The robot is remotely controlled using a wireless controller, while voltage and current sensors continuously monitor the electrical characteristics of both the photovoltaic system and the battery. Experimental measurements were conducted under different weather conditions to investigate the influence of solar irradiance on robot operating performance.

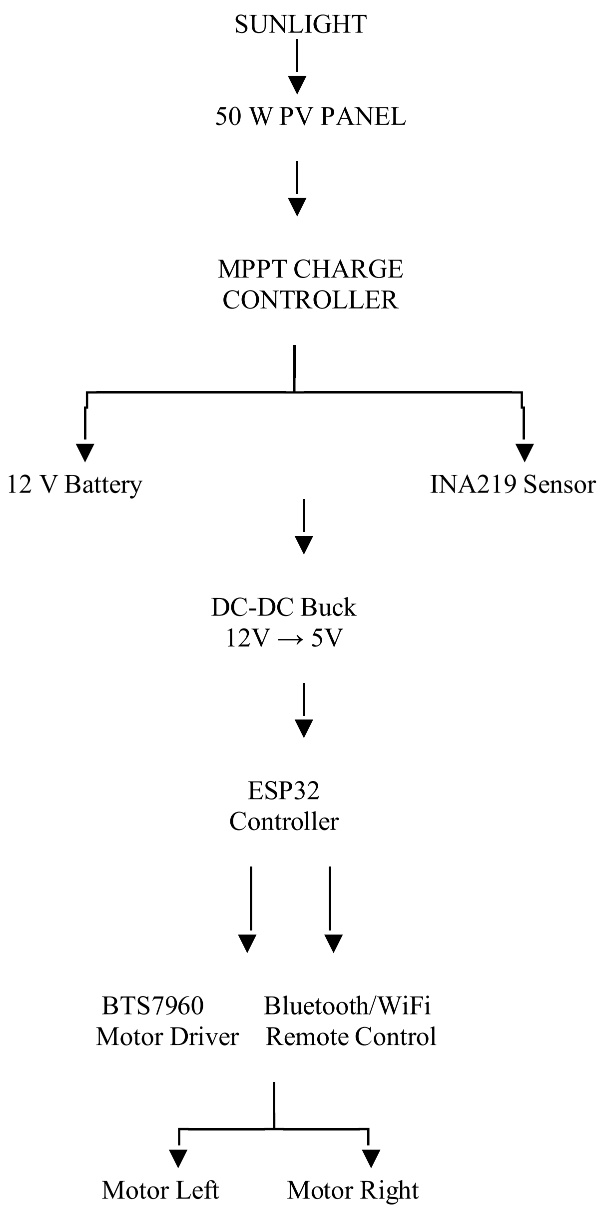

Figure 1. Electrical Schematic

50 W Solar Panel
(+) (-)

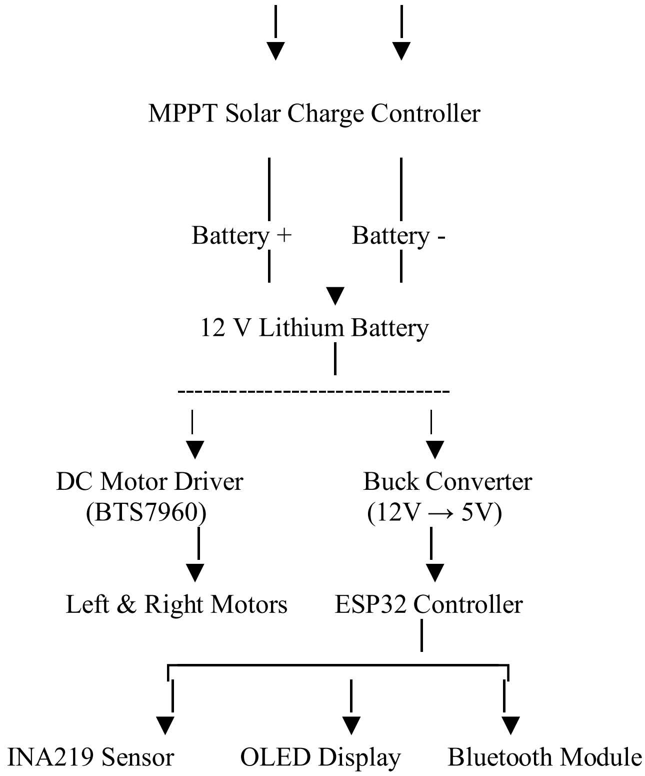

Figure 2. Electrical System Architecture

The Arduino Uno is an *open-source* platform, and Arduino is not only a development tool but also a combination of hardware, programming language, and IDE (Integrated Development Environment). An IDE is a software that has the function of writing programs, saving them, and uploading them to the microcontroller memory [19], [20]. HC-05 is an easy-to-use Bluetooth SPP (Serial Port Protocol) module for wireless serial communication that converts serial ports to Bluetooth HC-05 using Bluetooth V2.0 + EDR (Enhanced Data Rate) 3 Mbps modulation by utilizing 2.4 GHz radio waves [21]. The ACS712 Current Sensor is a Hall effect current sensor. The Allegro ACS712 Hall Effect is a precision sensor as an AC or DC current sensor in reading currents in the industrial, automotive, commercial, and communication systems. In general, this sensor application is usually used to control motors, electrical load detection, switched-mode power supplies, and overload protection [22]. A voltage sensor is a sensor that reads voltage and converts it into a small-scale DC voltage and is fed to a microcontroller [23], [24]. Step Up DC to DC is a voltage regulator that functions as a DC voltage regulator. If there is a DC voltage source that has a low voltage, using this tool, the low voltage can be increased by rotating the potentiometer on this tool [25], [26]. The 5V USB module is used to supply lithium batteries (Li-ion rechargeable batteries) with a current of 1 ampere. Two indicator lights have status conditions during the charging process or the entire situation. The 5V USB module uses an integrated circuit (IC) type TP4056, which works as a linear charger for single-cell lithium-ion batteries with constant current and voltage that has temperature regulation [27], [28], [29]. The research method that will be used to design and develop the implementation of a mobile remote control robot using Android-based solar panels.

2.1. Mechanical design

Mechanical design is something that must be done in designing a system on hardware. This integration is carried out by assembling based on the electrical design process and software design to mechanical design.

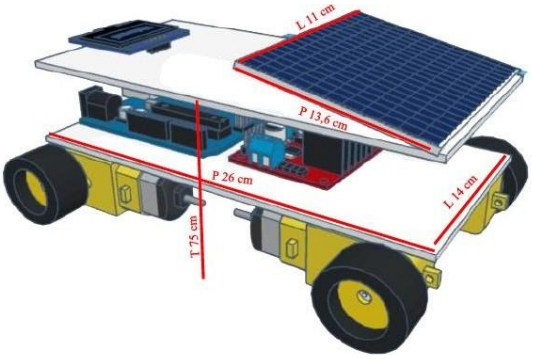

Figure 3. Mechanical Design

3. Result and Discussion

The results of this study are the implementation of a remote-controlled mobile robot using an Android-based solar panel by monitoring the voltage and current obtained by the 50WP solar panel, which is displayed in the robot's remote control and monitoring application. By implementing this 50WP solar panel. In this stage, it is explained how the designed system works. This system consists of several components with their respective functions. The Arduino Uno microcontroller is used for data processing, while the 50WP solar panel serves as the main power source. A ±9V battery is used as backup power, and the TP4056 module is used for battery charging. The XL6009 module functions to increase power. The ACS712 sensor and voltage sensor are used to collect voltage and current data from the solar panel, while the HC-05 module functions as a link between the application and the robot.

3.1. Solar Panel Results

Average results obtained when testing solar panels without using batteries.

Table 1. Test Results Without Battery

No	Day	Ampere (A)	Volt (V)
1	Saturday	3.71	11.67
2	Sunday	3.72	12.21
3	Monday	3.71	11.77
4	Tuesday	3.72	12.21
5	Wednesday	3.72	12.21
6	Thursday	3.72	11.77
7	Friday	3.72	11.37

Average results obtained when testing solar panels using batteries

Table 2. Test Results solar panels using Battery

No	Day	Ampere (A)	Volt (V)
1	Saturday	3.70	13.15
2	Sunday	3.72	13.25
3	Monday	3.73	13.2
4	Tuesday	3.71	13.25
5	Wednesday	3.72	13.2
6	Thursday	3.72	13.15
7	Friday	3.72	13.23

3.2. Results Remote Control Mobile Robot

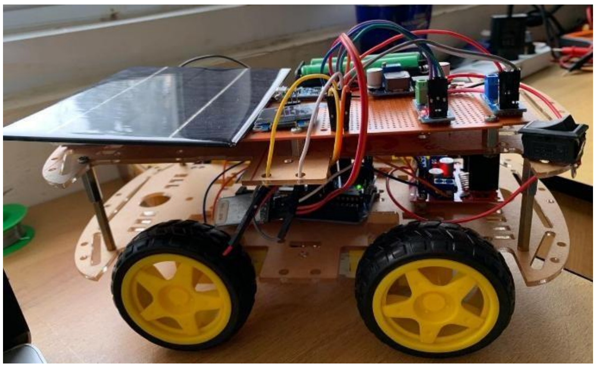

Figure 5. Remote Control Mobile Robot

Based on testing solar panels without batteries and with batteries, the following results were obtained:

Voltage Comparison Results

% Voltage Comparison = ($\frac{V_1 - V_2}{V_1} x\ 100^0/_0$ [22]

Where:

V1 = Voltage with Battery V2 = Voltage Without Battery

Using the formula above [22], the average percentage value of the voltage increase ($\bar{\nabla}$) on the solar panel can be determined.

Table 3. Solar Panel Voltage Comparison

No	Voltage Without Battery (V)	Voltage With Battery (V)	Average Voltage Increase Presentation (V)
1	11.67	13.15	11.25%
2	12.21	13.25	7.85%
3	11.77	13.2	10.83%
4	12.21	13.25	7.85%
5	12.21	13.2	7.50%
6	11.77	13.15	10.49%
7	11.37	13.23	14.06%

By measuring the voltage and current generated by the solar panel, we can ensure that the remote-controlled mobile robot is receiving the energy supply necessary to operate properly. These measurements also help optimize solar energy usage, thereby improving the efficiency and overall performance of the robotic system. The results of research conducted state that the torque generated during the experiment using 6V with the existing load, the robot was unable to move. After using a direct voltage of 12V, it was reduced to only 9V because the load on the battery itself was not only for the motor but also for other components. Therefore, with ± 9V, the robot could move according to its rotation. The experimental results confirm that integrating a 50 W photovoltaic panel significantly improves the energy performance of remotely controlled mobile robots operating outdoors. The photovoltaic system successfully reduced battery energy consumption, accelerated battery charging, and increased operational endurance without increasing fuel consumption or producing carbon emissions.

Compared with previous studies employing photovoltaic modules below 20 W, the proposed 50 W configuration supplied considerably higher electrical power, enabling simultaneous battery charging and robot operation during high irradiance periods. The incorporation of an MPPT charge controller further enhanced overall system efficiency by maintaining optimal operating conditions despite variations in solar intensity.

Nevertheless, photovoltaic-assisted robots remain highly dependent on weather conditions. Reduced solar irradiance during cloudy or rainy periods directly decreases available electrical power, thereby reducing charging capability and operational endurance. Future research should therefore investigate adaptive energy management algorithms capable of dynamically adjusting robot speed, mission planning, and power allocation according to real-time energy availability.

The integration of higher-efficiency photovoltaic modules, lightweight battery technologies, intelligent MPPT controllers, and artificial intelligence-based energy management systems is expected to further improve the sustainability of mobile robotic platforms. Moreover, combining photovoltaic systems with hybrid renewable energy sources may provide greater energy reliability for long-duration autonomous missions.

Overall, the proposed photovoltaic-assisted mobile robot demonstrates that renewable energy integration is technically feasible and capable of substantially enhancing operational performance. The findings contribute to the development of environmentally sustainable robotic systems suitable for surveillance, environmental monitoring, precision agriculture, infrastructure inspection, and disaster management applications.

4. Conclusion

This research aims to apply solar panels to a car-shaped robot controlled by an Android device. By comparing and measuring the voltage and current on the solar panel, the robot can operate properly. From various tests conducted, it was found that the voltage increased by 14.06% from 11.3V to 13.23V. In addition, the current also increased by 59.29% from 3.70A to 3.73A. Meanwhile, the highest measurement results with a battery showed a voltage of 13.88V and a current of 3.7A, with the robot being able to move. Overall, the integration of a 50 W photovoltaic system represents a practical and sustainable solution for improving the energy autonomy of remotely controlled mobile robots operating in outdoor environments. The proposed approach contributes to the development of environmentally friendly robotic systems capable of supporting long-duration applications such as environmental monitoring, security patrol, agricultural inspection, disaster response, and infrastructure surveillance.

Future research should focus on the implementation of intelligent energy management algorithms, high-efficiency photovoltaic modules, lightweight battery technologies, and hybrid renewable energy systems. In addition, integrating artificial intelligence for predictive energy optimization and autonomous mission planning is expected to further enhance the efficiency, reliability, and operational autonomy of solar-powered mobile robots.

5. Acknowledgement

We would like to thank the research and community service institute (LPPM) for funding this research.

References

[1] M. Soori, B. Arezoo, and R. Dastres, “Artificial intelligence, machine learning and deep learning in advanced robotics, a review,” Jan. 01, 2023, KeAi Communications Co. doi: 10.1016/j.cogr.2023.04.001.

[2] L. G. Divyanth et al., “Estimating depth from RGB images using deep-learning for robotic applications in apple orchards,” Smart Agricultural Technology, vol. 6, Dec. 2023, doi: 10.1016/j.atech.2023.100345.

[3] C. Zhuang et al., “Deep learning-based semantic segmentation of human features in bath scrubbing robots,” Biomimetic Intelligence and Robotics, vol. 4, no. 1, Mar. 2024, doi: 10.1016/j.birob.2024.100143.

[4] S. Zhou et al., “Neurosurgical robots in China: State of the art and future prospect,” Nov. 17, 2023, Elsevier Inc. doi: 10.1016/j.isci.2023.107983.

[5] M. L. Dezaki, S. Hatami, A. Zolfagharian, and M. Bodaghi, “A pneumatic conveyor robot for color detection and sorting,” Cognitive Robotics, vol. 2, pp. 60–72, Jan. 2022, doi: 10.1016/j.cogr.2022.03.001.

[6] U. Aulia, I. Hasanuddin, M. Dirhamsyah, and N. Nasaruddin, "A new CNN-BASED object detection system for autonomous mobile robots based on real-world vehicle datasets," Heliyon, vol. 10, no. 15, Aug. 2024, doi: 10.1016/j.heliyon.2024.e35247.

[7] S. Gon Park et al., "Deep Learning Model for Real-time Semantic Segmentation During Intraoperative Robotic Prostatectomy," Eur. Urol. Open Sci., vol. 62, pp. 47–53, Apr. 2024, doi: 10.1016/j.euros.2024.02.005.

[8] H. Sekkat, O. Moutik, B. El Kari, Y. Chaibi, T. A. Tchakoucht, and A. El Hilali Alaoui, "Beyond simulation: Unlocking the frontiers of humanoid robot capability and intelligence with Pepper's open-source digital twin," Heliyon, vol. 10, no. 14, Jul. 2024, doi: 10.1016/j.heliyon.2024.e34456.

[9] T. Sekine et al., "Robotic e-skin for high performance stretchable acceleration sensor via combinations of novel soft and functional polymers," Appl. Mater. Today, vol. 33, Aug. 2023, doi: 10.1016/j.apmt.2023.101877.

[10] J. Shanley et al., "Collaborative robotics to enable ultra-high-throughput IR-MALDESI," SLAS Technol., p. 100163, Jul. 2024, doi: 10.1016/j.slast.2024.100163.

[11] C. Qin, A. Song, H. Li, L. Zhu, X. Zhang, and J. Wang, "Overcoming the cognition-reality gap in robot-to-human handovers with anisotropic variable force guidance," Comput. Struct. Biotechnol. J., vol. 24, pp. 185–195, Dec. 2024, doi: 10.1016/j.csbj.2024.02.020.

[12] R. Fernandez-Fernandez, J. G. Victores, and C. Balaguer, "Deep Robot Sketching: An application of Deep Q-Learning Networks for human-like sketching," Cogn. Syst. Res., vol. 81, pp. 57–63, Sep. 2023, doi: 10.1016/j.cogsys.2023.05.004.

[13] J. Kim et al., "Macroscopic mapping of microscale fibers in freeform injection molded fiber-reinforced composites using X-ray scattering tensor tomography," Compos. B Eng., vol. 233, Mar. 2022, doi: 10.1016/j.compositesb.2022.109634.

[14] R. Fernandez-Fernandez, J. G. Victores, and C. Balaguer, "Deep Robot Sketching: An application of Deep Q-Learning Networks for human-like sketching," Cogn. Syst. Res., vol. 81, pp. 57–63, Sep. 2023, doi: 10.1016/j.cogsys.2023.05.004.

[15] E. Okafor, M. Oyedeji, and M. Alfarraj, "Deep reinforcement learning with light-weight vision model for sequential robotic object sorting," Journal of King Saud University - Computer and Information Sciences, vol. 36, no. 1, Jan. 2024, doi: 10.1016/j.jksuci.2023.101896.

[16] A. Da Rold, M. Furiato, A. M. A. Zaki, M. Carnevale, and H. Giberti, "Deep learning-based robotic sorter for flexible production," in Procedia Computer Science, Elsevier B.V., 2022, pp. 1579–1588. doi: 10.1016/j.procs.2022.12.358.

[17] P. Zheng, C. Li, J. Fan, and L. Wang, "A vision-language-guided and deep reinforcement learning-enabled approach for unstructured human-robot collaborative manufacturing task fulfilment," CIRP Annals, vol. 73, no. 1, pp. 341–344, Jan. 2024, doi: 10.1016/j.cirp.2024.04.003.

[18] M. R. Wilkinson, B. Castro-Dominguez, C. C. Wilson, and U. Martinez-Hernandez, "Low-cost, autonomous microscopy using deep learning and robotics: A crystal morphology case study," Eng. Appl. Artif. Intell., vol. 126, Nov. 2023, doi: 10.1016/j.engappai.2023.106985.

[19] E. U. Thoden van Velzen, Y. Workala, W. Teunissen, and I. Smeding, "Volatile organic contaminants in HDPE milk bottles along the mechanical recycling value chain, revealing origins and contamination pathways," J. Clean. Prod., vol. 459, Jun. 2024, doi: 10.1016/j.jclepro.2024.142571.

[20] V. B. Gjærum, I. Strümke, J. Løver, T. Miller, and A. M. Lekkas, "Model tree methods for explaining deep reinforcement learning agents in real-time robotic applications," Neurocomputing, vol. 515, pp. 133–144, Jan. 2023, doi: 10.1016/j.neucom.2022.10.014.

[21] P. Malvido Fresnillo, S. Vasudevan, W. M. Mohammed, J. L. Martinez Lastra, and J. A. Pérez García, "A method for understanding and digitizing manipulation activities using programming by demonstration in robotic applications," Rob. Auton. Syst., vol. 170, Dec. 2023, doi: 10.1016/j.robot.2023.104556.

[22] E. Kok and C. Chen, "Occluded apples orientation estimator based on deep learning model for robotic harvesting," Comput. Electron. Agric., vol. 219, Apr. 2024, doi:

10.1016/j.compag.2024.108781.

[23] S. Wang, J. Zhang, P. Wang, J. Law, R. Calinescu, and L. Mihaylova, “A deep learning-enhanced Digital Twin framework for improving safety and reliability in human–robot collaborative manufacturing,” Robot. Comput. Integr. Manuf., vol. 85, Feb. 2024, doi: 10.1016/j.rcim.2023.102608.

[24] S. C. Steinhaeusser and B. Lugrin, “Integrating sound effects and background music in Robotic storytelling – A series of online studies across different story genres,” Computers in Human Behavior: Artificial Humans, vol. 2, no. 2, p. 100085, Aug. 2024, doi: 10.1016/j.chbah.2024.100085.

[25] Y. Wu et al., “Vision-driven Collaborative Mobile Robotic Human Assistant System for Daily Living Activities,” in IFAC-PapersOnLine, Elsevier B.V., Jul. 2023, pp. 4400–4405. doi: 10.1016/j.ifacol.2023.10.1824.

[26] V. Sejdiu, A. Pajaziti, G. Rexha, X. Bajrami, E. Rrustemi, and J. Kola, “Detection, Recognition, and Grasping of Objects through Artificial Intelligence Using a Robotic Hand,” in IFAC-PapersOnLine, Elsevier B.V., Oct. 2022, pp. 443–446. doi: 10.1016/j.ifacol.2022.12.077.

[27] A. Z. Swartz, V. Novoa y Arruga Novoa, J. S. Hassoun, M. A. Crispens, and L. S. Prescott, “Robotic-assisted gynecologic surgery associated tympanic membrane perforation: A report of two cases and review of the literature,” Gynecol. Oncol. Rep., vol. 46, Apr. 2023, doi: 10.1016/j.gore.2023.101151.

[28] J. Dikobe, F. A. Melato, C. J. L. Adlem, and K. Netshiongolwe, “Determination of chromium species in water using diphenylcarbazide with a sequential spectrophotometric discrete robotic analyser,” Heliyon, vol. 10, no. 14, Jul. 2024, doi: 10.1016/j.heliyon.2024.e34670.

[29] Y. Zhao, X. An, and N. Sun, “Virtual simulation experiment of the design and manufacture of a beer bottle-defect detection system.,” Virtual Reality and Intelligent Hardware, vol. 2, no. 4, pp. 354–367, Aug. 2020, doi: 10.1016/j.vrih.2020.07.002.

[30] Z. Cai, Z. Feng, L. Zhou, X. Yang, and T. Xu, “Deep-reinforcement-learning-based robot motion strategies for grabbing objects from human hands,” Virtual Reality and Intelligent Hardware, vol. 5, no. 5, pp. 407–421, Oct. 2023, doi: 10.1016/j.vrih.2022.12.001.

[31] Y. Dmytriyev, M. Carnevale, and H. Giberti, “Enhancing flexibility and safety: collaborative robotics for material handling in end-of-line industrial operations,” in Procedia Computer Science, Elsevier B.V., 2024, pp. 2588–2597. doi: 10.1016/j.procs.2024.02.077.

[32] R. Aarthi and G. Rishma, “A Vision Based Approach to Localize Waste Objects and Geometric Features Exaction for Robotic Manipulation,” in Procedia Computer Science, Elsevier B.V., 2022, pp. 1342–1352. doi: 10.1016/j.procs.2023.01.113.