Journal of Applied Science, Engineering, Technology, and Education *ISSN: 2685-0591 (online)*
Vol. 8 No. 2 (2026)
https://doi.org/10.35877/454RI.asci2125

Tracking Objects with Mecanum Wheel Robot Cars using Computer Vision

Aan Darmawan Hangkawidjaja[a], Ratnadewi Ratnadewi[a*], Agus Prijono[a], Dasapta Erwin Irawan[b], & Satya Wibowo[a]

[a]*Universitas Kristen Maranatha, Bandung, Indonesia*
[b]*Institut Teknologi Bandung, Bandung, Indonesia*

Abstract

The purpose of this study is to describe the development of a mechanical wheeled robot car (using Mecanum wheels) that can follow an object via Computer Vision (CV). The object tracked is a regular 2-dimensional shape with a specific color (yellow), which can be attached to a person or moving object and followed by the robot at a set distance. The research methodology uses thr CV process, which begins by identifying the color of the object in the HSV (Hue, Saturation, and Value) color space, followed by shape recognition based on the number of contour keypoints obtained through Structural Analysis and Shape Descriptors. The outcomes of this combination enable the recognition of objects with a specific shape and color. To maintain the distance between the object and the robot, a calibration procedure is performed, and the distance between the robot's camera and the object is calculated using mathematical 2D distance calculations. This robot was built with a Single Board Computer (SBC) Raspberry Pi 4B+ controller (4GB memory and 32GB external memory), a Pi camera as the vision sensor, a Debian 11.0 "Bullseye" operating system, and a Python application, with assistance from the OpenCV library. According to test results on a yellow triangle-shaped object, the robot is able to track the movement of the object effectively, as intended, despite interference from objects with triangular shapes of different colors or objects of the same color.

Keywords: Mechanum Wheel, Computer Vision, HSV, Structural Analysis and Shape Descriptor

Received: 2 May 2026 Revised: 11 July 2026 Published: 31 August 2026

1. Introduction

Human following is a form of human-robot interaction for mobile robots. The mobile robot is used to track humans in the presence of occlusions and lighting changes, as well as to navigate with obstacle avoidance while following a target to a destination under state machine control. The Single Shot MultiBox Detector (SSD) is used to detect people, and color features are extracted using a color histogram to identify them. To avoid obstacles, the robot follows the target to its destination using a simultaneous localization and mapping (SLAM) technique with the LIDAR sensor. Experiments were conducted indoors with a large number of participants and mild lighting variations (Algabri & Choi, 2020).

In daily activities, for example, people with dementia or children walking around are often unmonitored, and parents are frequently concerned when the child's whereabouts or the person with dementia are unknown. As a result, it is important to use a detection device to track the location of children or individuals with dementia. The goal of this research is to develop a robot that can follow children or people with dementia using machine vision, which relies on visual input data.

Vision is the most powerful sense, providing a wealth of information about our environment and allowing us to interact intelligently with technologies without direct physical contact(Albdairi et al., 2022; Khalid et al., 2023). Vision enables us to determine the position and identity of objects, as well as their relationships. It is a highly sophisticated sense. The information from the sensor is a fragmented signal that requires further processing. In this study, fragmented data will be processed to provide valuable information for the robot to track the position(Das et al., 2022; Tsai & Yao, 2020).

Vision is the most powerful sense, providing a wealth of information about our environment and allowing us to interact intelligently with technologies without direct physical contact(Correia et al., 2016; Mayer, 2019). Vision enables us to

* Corresponding author.
E-mail address: aan.darmawan@eng.maranatha.edu

determine the position and identity of objects, as well as their relationships. It is a highly sophisticated sense. The information from the sensor is a fragmented signal that requires further processing. In this study, fragmented data will be processed to provide valuable information for the robot to track the position of a child or someone with dementia. The object whose color matches is then placed by the robotic arm at the designated location. According to experimental results, the developed robotic arm has an 80% accuracy rate in detecting colored items. It provides exceptional real-time measurement and shape identification accuracy, with 100% accuracy (Abdullah-Al-Noman et al., 2022; Balderas et al., 2024; Lubna et al., 2021; Taye, 2023).

Students in the Mechatronics Vocational Education program also learn about robot vision. They study the definition, design, development, and implementation of robots (Wahrini, 2023).

The utilization of computer vision for object detection includes several applications: face recognition, counting the number of objects in an image (Object Counting), automobile spotting (tracking in traffic), biometric detection (fingerprints, retinal prints, heart rate), medical diagnosis (object recognition to detect diseases such as tumors and cancer), OCR (Optical Character Recognition, for character recognition from document images), surveillance (security, CCTV cameras), and human-machine communication (recognition of human gestures and actions) (Masiado et al., 2025; Puri et al., 2018; Rosda et al., 2023).

The research in this article is part of a series of studies in the early stages of developing a human-detection robot; however, this study only involves object detection using simple contours. The next stage will involve human object detection using contoured attributes.

2. Method

The steps of the research method begin with a literature review, followed by the design of hardware and software, the acquisition of hardware components, the development of hardware and software robot tracking systems, robot testing, and system repair in the event of failures. A block diagram of the research process is shown in Figure 1.

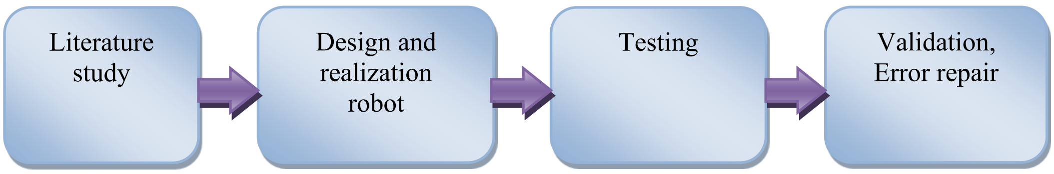


Figure 1. Diagram Block Research

2.1. Hardware Design

The object-tracking robot is physically designed as a four-wheel automobile robot with mechanical wheels (Williams, 2022), allowing for more flexible mobility (forward, backward, sideways to the left and right, turn left, turn right, and rotate). The robot is equipped with a Raspberry Pi camera (PiCam) for environmental monitoring and object tracking. The Raspberry Pi 4B+ SBC (Single Board Computer) serves as the CPU and controller, with 4GB of RAM and 32GB of SD card storage. The power source consists of four 18650 rechargeable Li-Ion batteries, with a voltage range of 3.7V and a capacity of 9000mAh. Figure 2 depicts the architecture of the wheel motor drive circuit connected to the Raspberry Pi.

Figure 2 illustrates the fundamental principle of the direction of motion of the Mecanum robot vehicle wheels relative to the robot car's movement. For example, in the top-left section of Figure 3, if all four wheels of the vehicle move forward, the robot car will travel forward. In the top-right section of Figure 3, if the two left wheels move in opposite directions (top-left wheel moves forward, bottom-left wheel moves backward), and the two right wheels also move in opposite directions (top-right wheel moves backward, bottom-right wheel moves forward), the robot car will shift horizontally to the right.

2.2. Object Tracking

The object-tracking robot is functionally designed and built to track items based on their color, shape, and the distance between them and the robot; it will follow the object with a preset color, shape, and distance(Chatrath et al., 2014; Kim et al., 2021; Zhang et al., 2022). The principle of color recognition is based on the HSV (Hue, Saturation, and Value) color model, which is used in the Robot World Cup, specifically for the soccer robot (Sugiarto et al., 2022). This model is preferred because the HSV model is more intuitive for human vision, while the RGB color model is better suited for display hardware (Srigul et al., 2016; Tuya, 2024; Yani et al., 2021). The color of the item to be recognized is captured using the upper and lower HSV values. Shape identification is accomplished through image processing by identifying the object's contour shape and then observing the number of contour points (for simple, regular object forms, each object shape has a unique number of points) (*OpenCV: Structural Analysis and Shape Descriptors*, 2009), using OpenCV's Structural Analysis and Shape Descriptors. The distance between the object and the robot is measured using the camera, which records the calculation of the object's contour area against a reference distance between the object and the camera (Fitrawan et al., 2020). Additionally, the distance between the item and the camera can be determined using the observed contour.

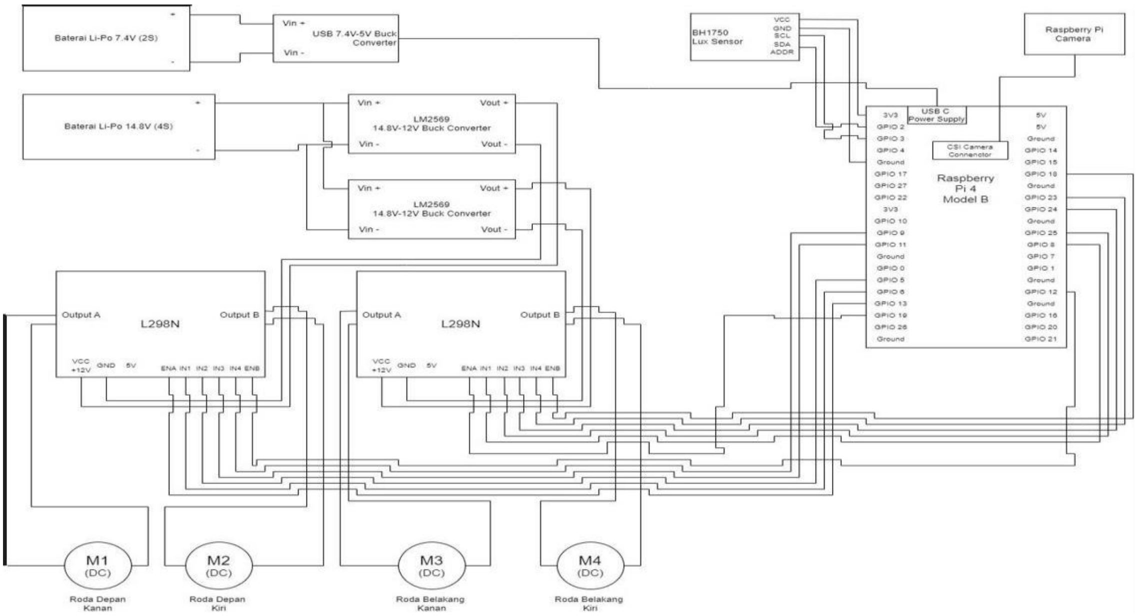


Figure 2. The wheel motor controller circuit Schematic on Raspberry Pi

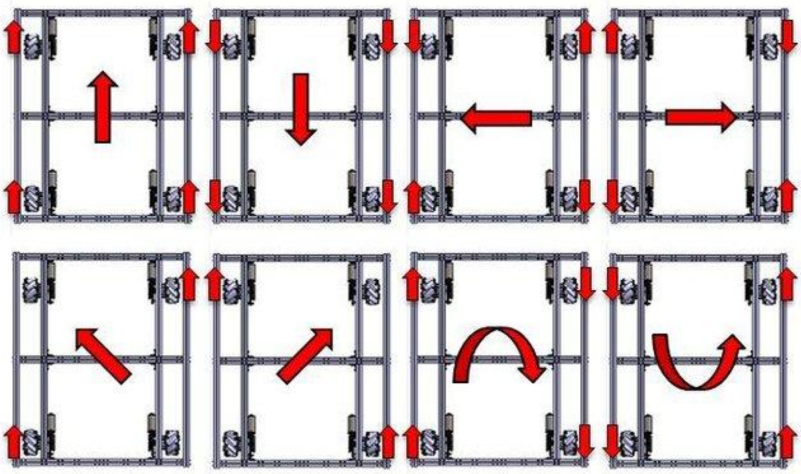
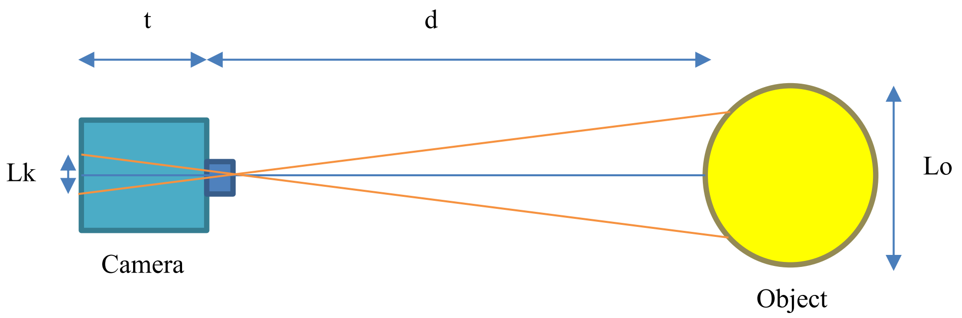


Figure 3. Motion direction of the robot car using mechanical wheels

The distance between the item and the camera can be calculated using the observed contour. The human-following robot car is based on research by P. Das et al. The four-wheel robotic vehicle system is equipped with a separate microcontroller unit and various sensors and modules, including ultrasonic and infrared sensors, which assist the robot's movement in relation to people and objects around it. This system detects the relative position of the mobile robot and the human. A four-wheel robotic vehicle system designed to follow humans incorporates various techniques, including human target detection, robot control algorithms, and obstacle avoidance. The robot is equipped with a separate microcontroller unit and several sensors and modules, including ultrasonic and infrared sensors, which assist in the robot's mobility in relation to humans and objects in its environment. This system detects the relative positions of the mobile robot and the human. Ultrasonic sensors are used to avoid obstacles and adjust the robot's distance from objects (Das et al., 2022). The distance between the camera and the object is calculated using the following formula:



$$\frac{f}{d} = \frac{Lk}{Lo} \quad (1)$$

$$f = (Lk * d)/Lo \quad (2)$$

$$d = (f * Lo)/Lk \quad (3)$$

Where:

Lo is width of object (cm)
Lk is width object as seen by the camera (pixel)
f is focal length
d is distance between camera and the object

To use the formula above, first calculate the focal length (f) by placing a circular object with a diameter of 3.5 cm (Lo) at a known distance—for example, 30 cm (d)—between the camera and the object. Next, the value of Lk is obtained by counting the number of pixels in the diameter of the circular object as seen in the image displayed on the monitor screen (the number of pixels is counted by the program). Using equation 2, f can be calculated based on the values of Lo, Lk, and d. This value of f is then substituted into equation 3.

Furthermore, using Equation 3, if the height of an object is known, the distance between the camera and the object can be calculated.

The contour area is used when the robot is 3 m away from an object; empirically, the robot still detects objects at distances of less than 3 m, so mathematical calculations and calibration have not yet been performed. (Table 3)

The descriptor used to analyze structure and shape is the Douglas-Peucker Algorithm, which simplifies the curves of an object. The number of points on the curves that make up the object's shape is reduced, while still preserving the curve's shape. This process is carried out recursively through the following steps: 1) Determine the start and end points of the object; 2) connect the start and end points from step 1 to form a line segment, then draw a perpendicular line from the line segment to a point on the curve; 3) for the result of step 2, determine the farthest distance from the line segment that touches the object; compare this distance to the threshold (epsilon); if the distance is greater than the threshold, identify that point. Epsilon (Tolerance): is a parameter that determines how close points must be to a line segment to be considered for removal. A smaller epsilon value will result in fewer points being removed, while a larger epsilon value allows for greater simplification. 4) Use the result from step 3 to split the curve into two new curves to be analyzed; then repeat steps 1 through 4 for each of these new curves. 5) Continue until all points are within the specified distance from the line segments.

OpenCV's approxPolyDP is used in this design to recognize shapes by calculating an object's contour points.

The Douglas–Peucker algorithm is powerful enough to simplify contours, reduce minor noise, preserve global shape, and work across various orientations. However, this algorithm is not well-suited as the sole method when the data contains significant partial occlusion, heavy noise, shape deformation, and requires robust object recognition.

This research is also based on ideas from prior studies, such as those conducted by Patoliya, Jignesh J., and Mewada, Hiren K., which address the interaction of robots with people in various social applications. The study focuses on the use of autonomous tracking algorithms and real-time tracking for robot automation. A feature set-based identity retention method is implemented and integrated into the robot's operating system. The tracking technique was developed using the Robot Operating System (ROS) on Linux, along with OpenCV. The tracking method achieved 85% accuracy and 72.3% precision (Patoliya & Mewada, 2019).

Amorim, Thulio G.S., et al. found that visual tracking is critical in mobile robotics. This work investigates three-dimensional target tracking using multi-robot visual data fusion. Collaborative visual tracking is tested, where input from multiple robots is combined using particle filters. To validate the method, non-collaborative visual tracking with data from a single robot is first employed. Next, collaborative visual tracking is tested, which involves combining data from multiple robots using a particle filter. To test both strategies, a visual tracking environment with partial occlusion—where tracking is performed by a collection of robots—is used. The experimental results reveal that the non-collaborative method has a lower computational cost than the collaborative method, but the inferred trajectory is disrupted by occlusion, which does not happen in the collaborative approach due to data fusion (Amorim et al., 2021).

Tsai, Tsung-Han, and Yao, Chia-Hsiang conducted research that identified the ability to detect and track specific humans as the primary technology for mobile robots. This study proposes real-time tracking, which uses stereo cameras to follow specific individuals in various environments. The tracking algorithm is designed to detect a specific target among a large number of people by combining block matching, human detection, and color histogram comparison. For real-world demonstrations, this research was carried out on a Raspberry Pi 4. The system employed can still operate at 20 FPS while maintaining good precision performance (Tsai & Yao, 2020).

Gad, Abdalla, and colleagues conducted research on recent breakthroughs in autonomous robotics with the goal of designing a reliable system capable of detecting and tracking multiple objects in the surrounding environment for navigation and guidance. This study includes several object tracking (MOT) algorithms that combine various inputs from sensors such as cameras and light detection and ranging (LiDAR). The journal provides an overview of the most common benchmark metrics and datasets used for MOT training and performance evaluation, such as the Karlsruhe Institute of Technology and Toyota Institute of Technology (KITTI), MOTChallenges, and the University at Albany DEtection and TRACking (UA-DETRAC) (Gad et al., 2022).

Figure 4 shows the process of determining the HSV lower and upper values for the yellow circle object by sliding the trackbar. The HSV lower value is 23, 95, 110, and the HSV upper value is 52, 255, 255.

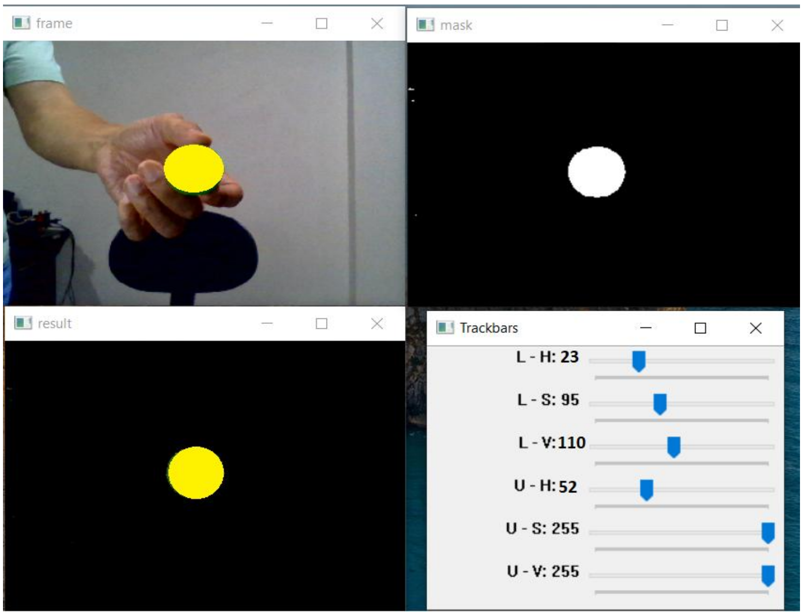


Figure 4. The process of finding the HSV upper value and HSV lower value

Figure 5 shows the different numbers of contour points based on the shape of the object. For example, a triangle has 3 contour points, a square has 4 contour points, an arrow has 7 contour points, a circle has 8 contour points, and a star has 10 contour points.

Figure 5. Number of contour points depending on the shape of the object

Figure 6 depicts a reference photo of the object at a distance of up to 30 cm, with the object being a yellow circle with a diameter of 3.5 cm. The reference photo is then converted to the HSV color space and masked against the yellow color, with the upper and lower HSV values recorded as a reference for the object's color filter and distance.

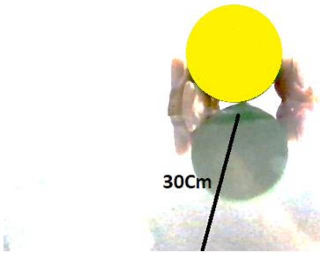


Figure 6. Reference photo of the object at a distance of 30 cm from the Camera

2.3. Robot Motion Settings

The motion scenario of the robot car is set based on the position of the object monitored through the monitoring window which is 640x480 pixels in size, the direction of the robot's motion towards the position of the object can be seen in Figure 7. If the position of the object with respect to the x-axis, is in the region 256<=x<=384 the robot will stand still. If the object position is in the region 128<x<=256 the robot will move to the left. If the position of the object is in the region 0 < x <= 128 the robot will rotate towards the left, the same applies to the state of the object's position in the right area.

The inspiration for the car robot motion scenario is regulated based on the position of the object monitored through the monitoring window obtained from research conducted by Zanchettin, Andrea Maria, regarding the application of a cage-less robot with a safe sensor output processing method and aims to maximize robot productivity in collaborative scenarios. In particular, the strategy of speed and separation monitoring (SSM: Speed and Separation Monitoring), which requires slowing down the robot's movement compared to human distance (Zanchettin, 2023).

The method of recognizing and tracking objects by mobile robots has been carried out by V. Yevsieiev et al. in real time. Here, color is used in the detection process according to algorithms and mathematics. This method was implemented in Python using the PyCharm development environment (Yevsieiev et al., 2023).

The forward/backward movement of the robot car is set as follows, assuming s is the distance between the robot car and the object, then 100 cm <=s <=150 cm the robot car will stand still, if s <100 cm the robot will move backwards away from the object, otherwise if s> 150 cm the robot will move forward towards the object.

Figure 8 shows the flowchart of the object-tracking robot controller program. The environment in front of the robot will be monitored through a camera, the image captured by the camera is pre-processed by removing noise through a Gaussian Blur filter. Furthermore, the image color is transferred from the RGB field to the HSV field, and color masking is performed on the image. The masked image is restored through the Erode and Threshold process to facilitate the search for object contours. The next stage is looking for object contours, if found, it will be checked whether the area is greater than 300 pixels.

The value of 300 is the result of an experiment to distinguish the size of the target object from the noise object. If the object area is found to be greater than 300, then the object is checked for the number of contour points. If the number of contour points is equal to 3 then it is considered a tringle object (the intended object). Then the position of the object is checked, if the object is in the center of the observation area, the robot is stationary. If the object is to the left of the observation area (see Figure 8) the robot is shifted to the left. If the object is to the right of the monitored area, the robot is shifted to the right so that the position of the object is always in the center of the monitored area.

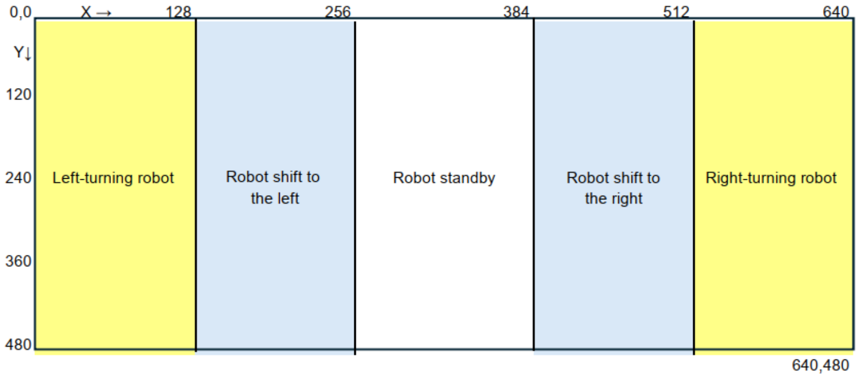


Figure 7. Robot motion direction based on object position

The next stage is calculated the distance between the object and the camera, if the distance is <100 cm (considered too close) then the robot will move backwards away, if the distance is >150 cm (considered too far) then the robot will move forward closer. This is done continuously as long as the program is not stopped.

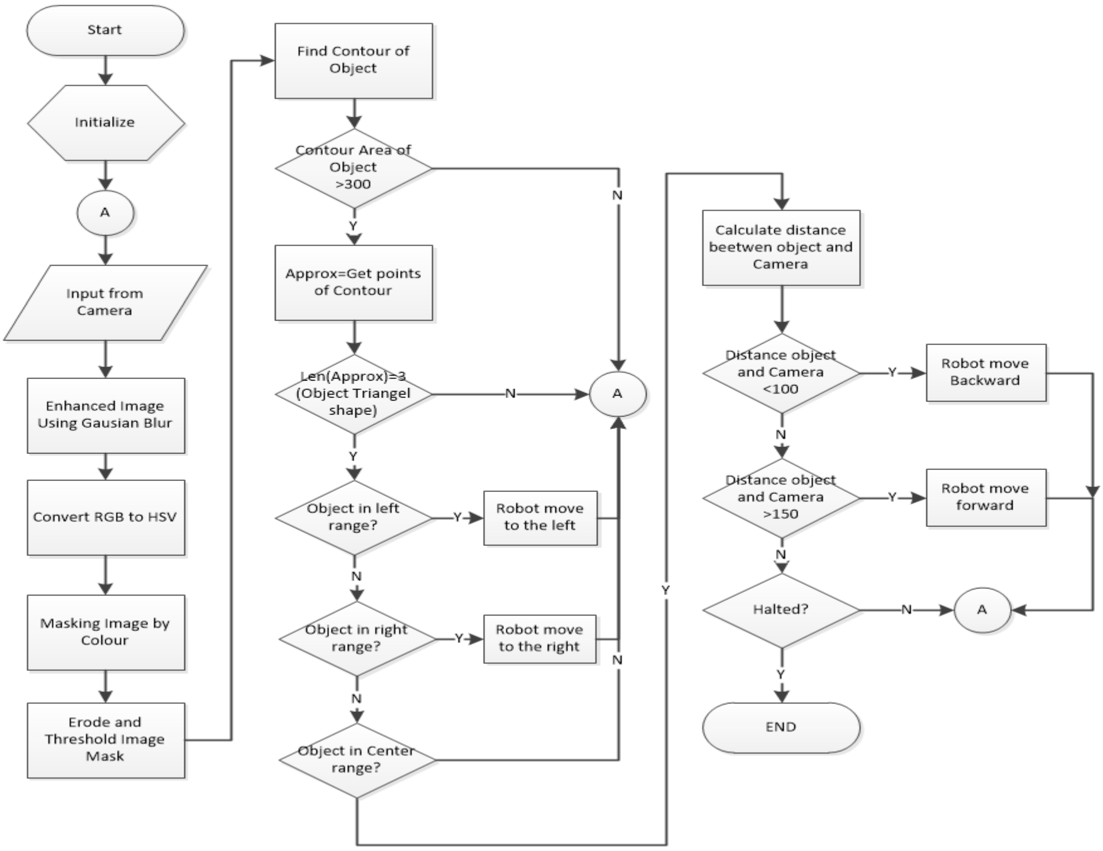


Figure 8. Flowchart of object-tracking robot controller program

3. Results and Discussion

Figure 9 shows a photo of the realization of the human-following robot car.

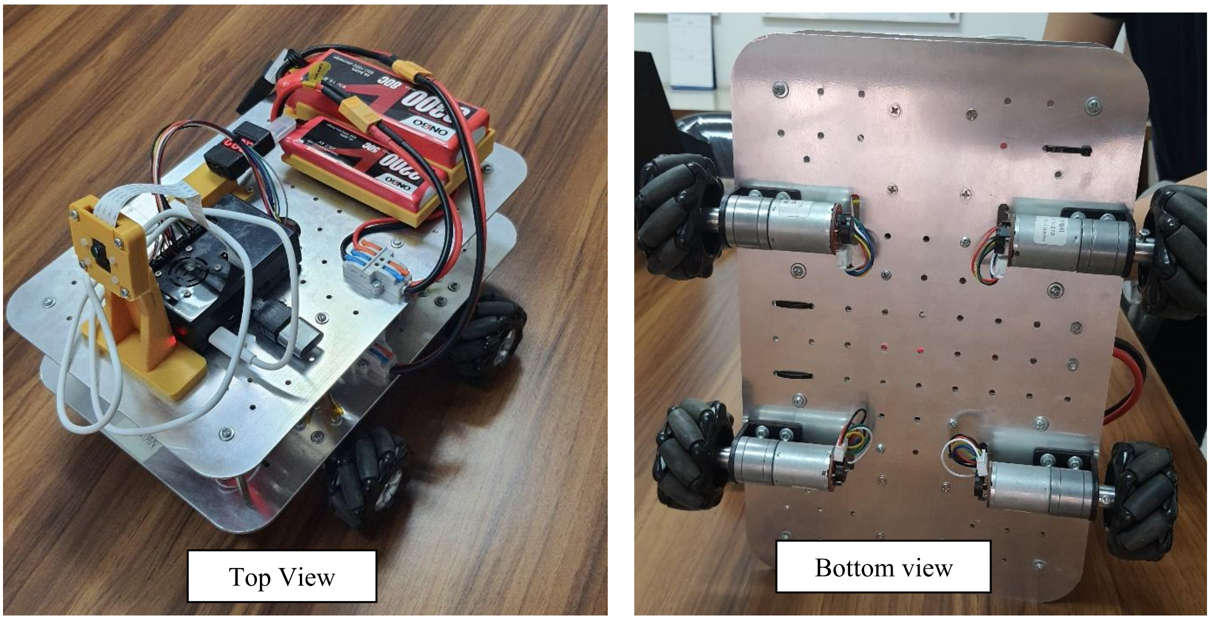


Figure 9. photo of realization of robot car using mechanical wheels

The design of this robot consists of four stages, namely:

a. The first stage is the color calibration stage, which determines whether the detected color is yellow, green, red, or blue by analyzing the HSV values of each color. The HSV values for the color yellow are defined as the color the robot will identify.
b. The second stage involves implementing the HSV value for the color yellow into the robot's program so that when the robot detects the color yellow, it will follow the yellow object.
c. The third stage is the object shape calibration stage, which determines whether the object is triangular, square, or circular. In this design, a triangular shape was selected.
d. The fourth stage involves combining the recognition of yellow, circular objects. Thus, if the robot detects a yellow, triangular object, it will follow that object.

Empirical testing was directly applied to this design. While color and shape recognition can be performed for various colors and shapes, this design intentionally selected yellow, triangular objects.

In this study, experiments have been conducted on: limited variations in lighting (Table 1), object distance (Table 3), background clutter, and different object shapes and colors (Table 2).

However, experiments on variations in object movement speed have not yet been conducted.

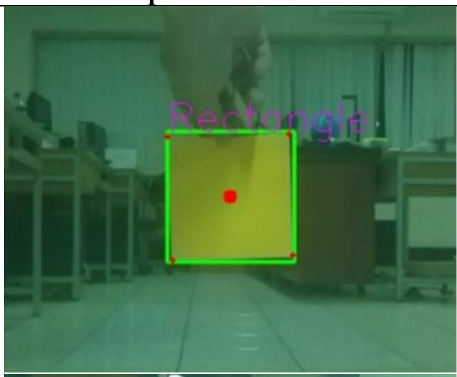
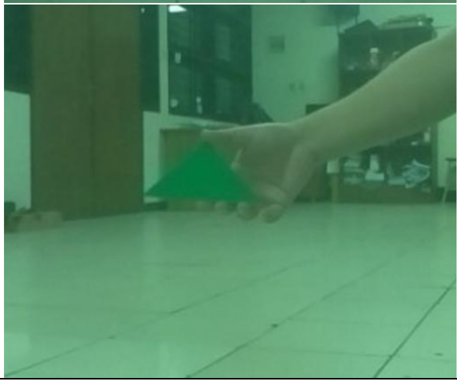
At first, the robot car was trained to recognize the color yellow. The robot is set to work in 3 lux value regions and the results of the HSV value range that detects yellow color can be seen in Table 1.

Table 1. HSV values and Lux conditions

H	S	V	Lux meter (lux)
23-52	96-255	110-255	25-71 70-130 375-579

Table 1's HSV values allow the robot to recognize the color yellow regardless of its shape. Table 2 displays the findings of the robot's color vision.

Table 2. Results of the robot's color vision

No	Purpose of the experiment	Photos of Experiment Results	Detection result
1	Robot is trained to identify yellow color.		The robot can identify yellow objects and generate boundary boxes for box-shaped things.
2	Robot trained to detect yellow color		The robot does not recognize the color yellow, and because the object is green, the robot does not produce a bounding box.

The results of form and color recognition can be observed in Figure 10, which displays the results of the yellow, circular, and distance (measured 12.5 cm) object recognition program, which is the foundation of robot object tracking.

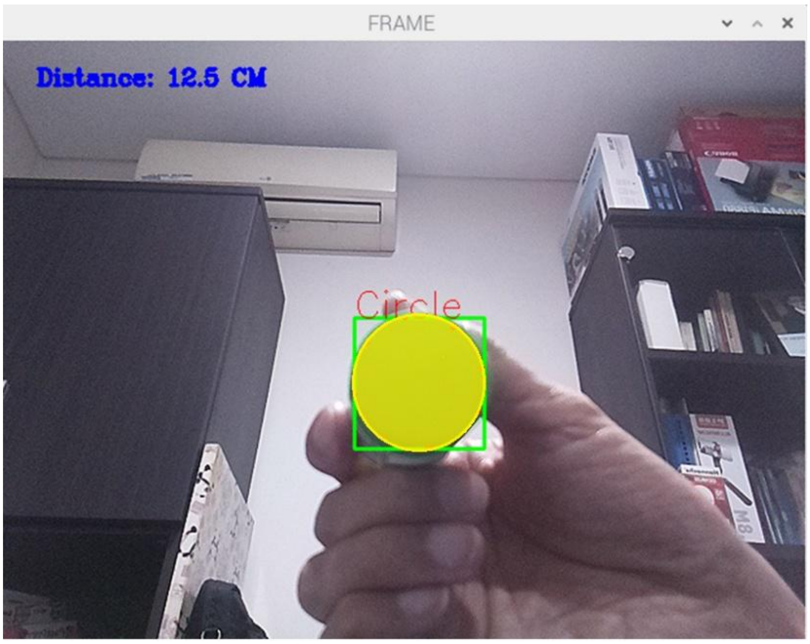


Figure 10. shows the results of recognizing the shape, color, and distance of a yellow circle object.

The next test involved determining the maximum distance of object detection based on the minimal amount of pixels in a contour. Table 3 displays the outcomes of this test. When the lux sensor detects a value in column 1, and the minimum number of pixels of a yellow object in column 2, the robot vision can detect a yellow object from a maximum distance of column 3.

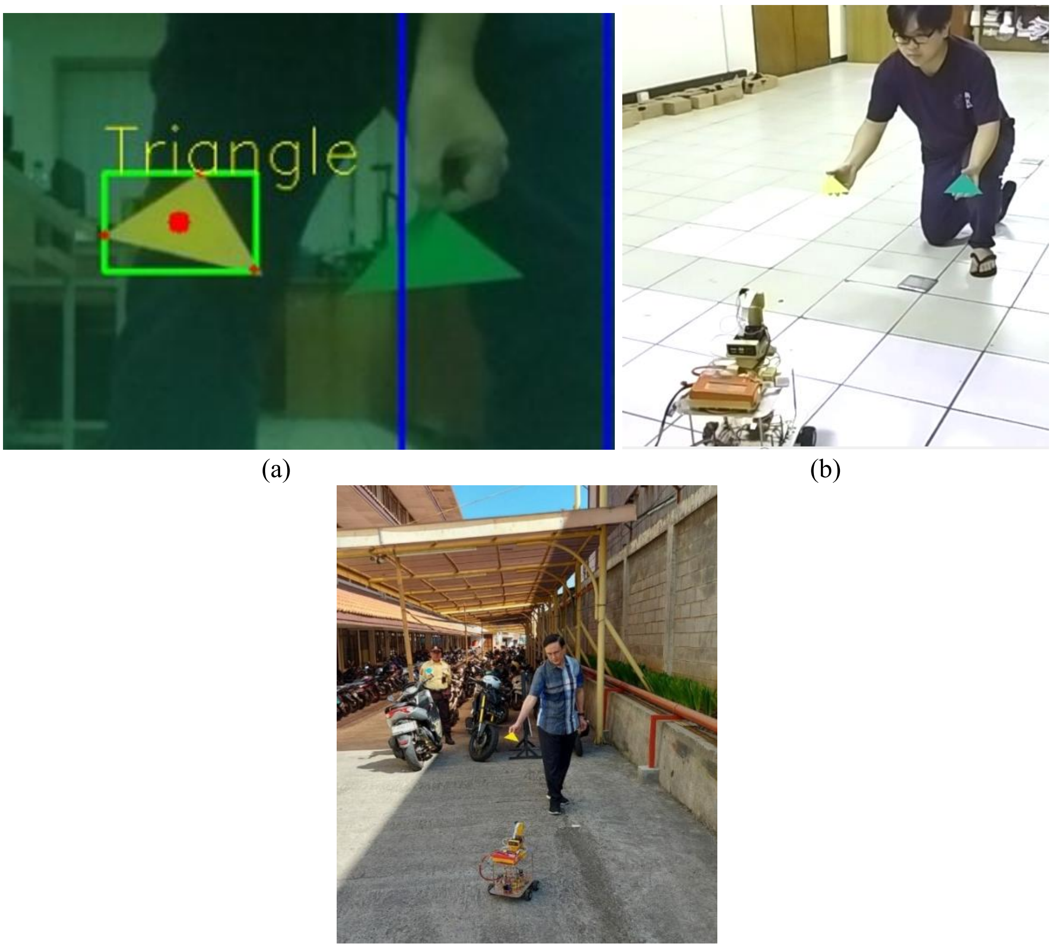
Table 3. Maximum Distance Trial of Object Detection Based on Contour i.e. minimum number of pixels.

Lux	Contour (minimum number of pixels)	Maximum distance detected (cm)
68	100	270
69	300	171
70	600	125

After all attempts to detect color, shape, and distance were successful, the robot was set to detect only yellow, triangular objects.

3.1. Testing Results

The test was carried out by attaching a yellow triangular object to the respondent, then the respondent is 150cm away from the robot car and moves the road in various directions at low speed (about 1m / sec) in a 100 lux light environment, the results of the robot can follow well as expected. Figure 11 shows the detection results of the robot, the robot successfully followed the yellow-colored and triangular-shaped object. When the object is yellow and triangular, the robot car will follow where the object moves, but if the green and triangular object is moved, the robot just stays still, not following the object. Figure 11(a) the robot's vision when following a yellow and triangular object; Figure 11(b) the indoor experiment; and Figure 11(c) the outdoor experiment.



(a) (b)

(c)

Figure 11. Experimental photos of 1 yellow triangle and 1 green triangle (a) robot vision (b) indoor experiment (c) outdoor experiment

4. Conclusion

This study successfully designed, implemented, and evaluated an object-tracking robot car based on Mecanum wheel technology and computer vision techniques. The proposed system integrates a Raspberry Pi 4B+ single-board computer, Pi Camera, OpenCV image processing libraries, and a Mecanum wheel locomotion mechanism to create a mobile robot capable of autonomously tracking designated objects. The developed tracking approach combines HSV color segmentation, contour-based shape recognition, and distance estimation using contour area analysis to enable reliable identification and tracking of a target object in real time.

The experimental results demonstrate that the HSV color model is effective for distinguishing the target object from the surrounding environment under varying illumination conditions. Calibration experiments established an optimal HSV range for yellow object detection, allowing the robot to consistently recognize the intended color in lighting environments ranging from approximately 25 lux to 579 lux. Furthermore, the Structural Analysis and Shape Descriptor approach successfully differentiated geometric shapes based on contour points, enabling the system to distinguish triangular objects from other shapes such as circles, squares, arrows, and stars. This dual-filtering mechanism, which combines both color and shape information, significantly improved object identification reliability and reduced false detections.

The distance measurement mechanism based on contour area also demonstrated satisfactory performance. Experimental testing showed that the robot could detect target objects at varying distances depending on the contour size threshold. Larger contour areas resulted in more stable and accurate distance estimation, while smaller contour thresholds enabled longer-range detection. The findings indicate that contour-based distance estimation provides a practical and computationally efficient solution for low-cost mobile robot applications that do not require dedicated distance sensors.

The integration of object position monitoring and motion control enabled the Mecanum wheel robot to maintain the target object within the center region of the camera frame while simultaneously regulating the distance between the robot and the object. The omnidirectional movement capability provided by the Mecanum wheel configuration allowed the robot to perform lateral movements, rotations, and forward-backward adjustments without requiring complex turning maneuvers. This mobility characteristic contributed significantly to smooth and responsive object-following behavior.

Performance evaluation through indoor and outdoor experiments confirmed that the robot successfully tracked a yellow triangular target attached to a moving person. The system maintained stable tracking performance when the target moved at low speed and correctly ignored distractor objects that shared either the same shape or the same color but not both simultaneously. These results demonstrate the effectiveness of combining color and shape recognition as a robust object-tracking strategy for mobile robotic applications.

From a practical perspective, the developed robot has potential applications in assistive technologies, child monitoring, elderly care, educational robotics, and autonomous service robots. The use of affordable hardware components and open-source software frameworks also makes the proposed system suitable for robotics education and research environments, particularly in vocational and engineering institutions.

Despite the promising results, several limitations remain. The current system relies on predefined color and geometric shape characteristics, making it less adaptable to complex real-world environments containing dynamic lighting conditions, occlusions, or multiple similar objects. Future research should explore the integration of advanced artificial intelligence techniques such as deep learning-based object detection, multi-object tracking, semantic scene understanding, and sensor fusion using LiDAR or ultrasonic sensors. In addition, implementing obstacle avoidance, adaptive distance control, and human recognition algorithms would further enhance the robot's autonomy and applicability in real-world scenarios.

Overall, the study demonstrates that the integration of computer vision, HSV-based color recognition, contour-based shape analysis, and Mecanum wheel mobility can produce an effective, low-cost, and reliable object-following robot capable of performing real-time tracking tasks in both indoor and outdoor environments. This work provides a solid foundation for future developments in intelligent mobile robotics and autonomous human-following systems.

Acknowledgments: We wish to thank the supported by Universitas Kristen Maranatha, Indonesia.

References

Abdullah-Al-Noman, M., Eva, A. N., Yeahyea, T. B., & Khan, R. (2022). Computer Vision-based Robotic Arm for Object Color, Shape, and Size Detection. *Journal of Robotics and Control (JRC)*, *3*(2), 180–186. https://doi.org/10.18196/jrc.v3i2.13906

Albdairi, A. J. A., Xiao, Z., Alkhayyat, A., Humaidi, A. J., Fadhel, M. A., Taher, B. H., Alzubaidi, L., Santamaría, J., & Al-shamma, O. (2022). Face Recognition Based on Deep Learning and FPGA for Ethnicity Identification. *Applied Sciences (Switzerland)*, *12*(5). https://doi.org/10.3390/app12052605

Algabri, R., & Choi, M.-T. (2020). Deep-learning-based Indoor Human Following of Mobile Robot Using Color Feature. *Sensors*, *20*(2699), 19.

Amorim, T. G. S., Souto, L. A., P. Do Nascimento, T., & Saska, M. (2021). Multi-Robot Sensor Fusion Target Tracking with Observation Constraints. *IEEE Access*, *9*, 52557–52568. https://doi.org/10.1109/ACCESS.2021.3070180

Balderas, L., Lastra, M., & Benítez, J. M. (2024). Optimizing Convolutional Neural Network Architectures. *Mathematics*, *12*(19), 1–25. https://doi.org/10.3390/math12193032

Chatrath, J., Gupta, P., Ahuja, P., Goel, A., & Arora, S. M. (2014). Real time human face detection and tracking. *2014 International Conference on Signal Processing and Integrated Networks, SPIN 2014*, 705–710. https://doi.org/10.1109/SPIN.2014.6777046

Correia, C., Lopez, K. J., Wroblewski, K. E., Huisingh-Scheetz, M., Kern, D. W., Chen, R. C., Schumm, L. P., Dale, W., McClintock, M. K., & Pinto, J. M. (2016). Global sensory impairment in older adults in the United States. *Journal of the American Geriatrics Society*, *64*(2), 306–313. https://doi.org/10.1111/jgs.13955

Das, P., Biswas, A., Pal, A., Das, R., Mahato, D. R., Mondal, J. P., Biswas, J., Saha, A., & Ghosh, A. (2022). Human Following Robot. *International Journal of Creative Research Thoughts (IJCRT)*, *10*(3), 174–185. https://doi.org/10.54389/yefj9778

Fitrawan, A. A., Shodiq, M. N., Kusuma, D. H., & Jannah, F. R. U. (2020). Sistem Pendeteksi Jarak Pada Objek Realtime Video Berdasarkan Luas Kontur Menggunakan Metode Circle Hough. *Seminar Nasional Terapan Riset Inovatif (SENTRINOV)*, *6*(1), 935–942.

Gad, A., Basmaji, T., Yaghi, M., Alheeh, H., Alkhedher, M., & Ghazal, M. (2022). Multiple Object Tracking in Robotic Applications: Trends and Challenges. *Applied Sciences (Switzerland)*, *12*(19). https://doi.org/10.3390/app12199408

Khalid, M., Sarfraz, M. S., Iqbal, U., Aftab, M. U., Niedbała, G., & Rauf, H. T. (2023). Real-Time Plant Health Detection Using Deep Convolutional Neural Networks. *Agriculture*, *13*(2), 510. https://doi.org/10.3390/agriculture13020510

Kim, Y. Y., Kim, H., Lee, W., Choi, H. L., & Moon, I. C. (2021). Black-box expectation–maximization algorithm for estimating latent states of high-speed vehicles. *Journal of Aerospace Information Systems*, *18*(4), 175–192. https://doi.org/10.2514/1.I010831

Lubna, Mufti, N., & Shah, S. A. A. (2021). Automatic Number Plate Recognition:A Detailed Survey of Relevant Algorithms. *Sensors*, *21*(9), 3028. https://doi.org/10.3390/s21093028

Masiado, S. L., Constantino, A. D., Cajurao, J. F., Valenciano, J. V., Lagayao, J. V., Dasmariñas, J. S. S., & Laud, R. J. S. (2025). GrainBot: An Android-Controlled Rice Grain Collector Robot. *International Journal of Advanced Science Computing and Engineering*, *7*(2), 60–70. https://doi.org/10.62527/ijasce.7.2.258

Mayer, R. E. (2019). Computer Games in Education. *Annual Review of Psychology*, *70*(1), 531–549. https://doi.org/10.1146/annurev-psych-010418-102744

OpenCV: Structural Analysis and Shape Descriptors. (2009). https://doi.org/10.1007/978-3-031-02186-2_4

Patoliya, J. J., & Mewada, H. K. (2019). Automated tracking and real time following of moving person for robotics applications. *Journal of Automation, Mobile Robotics and Intelligent Systems*, *13*(4), 31–37. https://doi.org/10.14313/JAMRIS/4-2019/35

Puri, R., Gupta, A., & Sikri, M. (2018). Contour, Shape, and Color Detection Using Open CV-Python. *International Journal of Advances in Electronics and Computer Science*, *5*(3), 2393–2835.

Rosda, R., Wali, M., & Imilda, I. (2023). Evaluation of the Successful Implementation of the SIMARDI Using the Technology Acceptance Model (TAM). *SAGA: Journal of Technology and Information System*, *1*(2), 56–63. https://doi.org/10.58905/saga.v1i2.67

Srigul, W., Inrawong, P., & Kupimai, M. (2016). Plastic classification base on correlation of RGB color. *2016 13th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, ECTI-CON 2016*, 1–5. https://doi.org/10.1109/ECTICon.2016.7561304

Sugiarto, K., Giyantara, A., & Yulisya, R. D. (2022). Object Tracking Dengan Menggunakan Color Filtering HSV Pada Robot World Cup. *Jurnal Bumigora Information Technology (BITe)*, *4*(2), 143–152. https://doi.org/10.30812/bite.v4i2.2156

Taye, M. M. (2023). Theoretical Understanding of Convolutional Neural Network: Concepts, Architectures, Applications, Future Directions. *Computation*, *11*(3). https://doi.org/10.3390/computation11030052

Tsai, T. H., & Yao, C. H. (2020). A robust tracking algorithm for a human-following mobile robot. *IET Image Processing*, *15*(3), 786–796. https://doi.org/10.1049/ipr2.12062

Tuya. (2024). *HSV and RGB-TuyaOS-Tuya Developer*. Tuya Inc.

Wahrini, R. (2023). Development of Color-Based Object Follower Robot Using Pixy 2 Camera and Arduino to Support Robotics Practice Learning. *Jurnal Edukasi Elektro*, *7*(2), 161–168. https://doi.org/10.21831/jee.v7i2.64413

Williams, A. (2022). *All about Mecanum|Hackaday*.

Yani, I., Resti, Y., Burlian, F., & Ansyori. (2021). Prediction of Plastic-Type for Sorting System using Fisher Discriminant Analysis. *Science and Technology Indonesia*, *6*(4), 313–318. https://doi.org/10.26554/sti.2021.6.4.313-318

Yevsieiev, V., Abu-Jassar, A., & Maksymova, S. (2023). Object Recognition and Tracking Method in the Mobile Robor's Workspace in Real Time. *Technical Science Research in Uzbekistan*, *2*(2), 356–363.

Zanchettin, A. M. (2023). 2023 Andrea Mariag Zanchettin Human tracking from quantised sensors_ ...tion to safe human–robot collaboration.pdf. *Control Engineering Practice*, *141*(105727). https://doi.org/https://doi.org/10.1016/j.conengprac.2023.105727

Zhang, W., Gao, X. zhong, Yang, C. fu, Jiang, F., & Chen, Z. yuan. (2022). A object detection and tracking method for security in intelligence of unmanned surface vehicles. *Journal of Ambient Intelligence and Humanized Computing*, *13*(3), 1279–1291. https://doi.org/10.1007/s12652-020-02573-z