

Optimization of Machine Learning-Based Automatic Target Detection and Locking System on Robots

Received:
10 December 2023

Accepted:
27 August 2024

Published:
31 August 2024

¹Mokhammad Syafaat, ^{2*}Siti Sendari, ³Ilham Ari Elbaith Zaeni,
⁴Samsul Setumin

¹⁻³ *Electrical Engineering and Informatics, Universitas Negeri Malang,*

¹ *Teknik Elektronika Sistem Senjata, Politeknik Angkatan Darat,*

⁴ *Faculty of Electrical Engineering, Universiti Teknologi MARA (UiTM)
Pulau Pinang*

*E-mail: ¹syafaatarh96@poltekad.ac.id, ²siti.sendari.ft@um.ac.id,
³ilham.ari.ft@um.ac.id, ⁴samsuls@uitm.edu.my*

*Corresponding Author

Abstract—Background: In recent years, the world of robotics has made significant progress in improving the operational capabilities of robots through target detection and locking systems. These systems play a crucial role in improving the efficiency and effectiveness of critical applications such as defense, security, and industrial automation. However, the main challenge faced is the limitations of the existing system in adapting to unstable environmental conditions and dynamic changes in targets. **Objective:** This research aims to overcome these challenges by developing a more adaptive and responsive target detection and locking system by integrating two leading machine learning technologies: Convolutional Neural Networks (CNN) for target detection and Long Short-Term Memory (LSTM) for target tracking. **Methods:** This study uses a quantitative approach to evaluate the effectiveness of the integration of CNNs and LSTMs in target detection and locking systems. **Results:** The results of the study showed a detection accuracy rate of 95% and a locking accuracy of 90%. The system is proven to be able to adapt to changing operational conditions in real-time and provide consistent performance in a variety of complex and dynamic scenarios. **Conclusion:** The conclusion of this study is that the integration of CNN and LSTM technologies in target detection and locking systems in robots significantly improves the performance and efficiency of the system, enabling a wider and more complex application.

Keywords— Robotics; Target Detection; Target Locking; Image Processing; CNN; LSTM

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Corresponding Author:

Siti Sendari,
Electrical Engineering and Informatics,
Universitas Negeri Malang,
Email: siti.sendari.ft@um.ac.id
Orchid ID: <https://orcid.org/0000-0002-8681-7024>



I. INTRODUCTION

Robotics technology has succeeded in improving the operational capabilities of robots through target detection and locking systems. This innovation is one of the leading innovations, especially in applications such as defense, security, and industrial automation[1]. This system is very important because it can increase efficiency and effectiveness in such a wide range of critical applications. Although much progress has been made, existing systems are often hampered by limited adaptation to unstable environmental conditions and dynamic changes in targets[2][3].

Previous studies have focused on single machine learning algorithms but have often failed to address the complexity of the actual operational environment. Such algorithms tend to be less flexible in responding to unexpected variations in target behavior or fluctuations in light and visual conditions[4][5]. For example, in studies that use only one type of algorithm, machine learning often faces difficulties in detecting targets in environments with changing lighting or when the target moves in unexpected ways. This approach shows shortcomings in dealing with complex real-world challenges[6][7][8].

This combination not only improves detection and lockout accuracy in a variety of scenarios[9], but also allows the system to adapt in real-time to changing operational conditions[10][11]. For example, CNNs can detect targets with high accuracy even in poor lighting conditions, while LSTMs can track the target's movement continuously even if the target performs unexpected maneuvers. The uniqueness of this research lies in the combination of these two technologies, which provides a more dynamic and adaptive solution than conventional approaches[12], [13], [14].

This research provides a more dynamic and adaptive solution than conventional approaches. This integration creates a synergy between static destination recognition and dynamic tracking, improving the overall responsiveness and reliability of the system in the face of fluctuating operational conditions and fast-moving destinations[15], [16], [17], [18]. For example, previous research by Zhang et al. (2020) only used CNNs for target detection, but was not able to track fast-moving targets well[19]. Meanwhile, research by Lee et al. (2019) [20], [21] that uses LSTM for target tracking, shows limitations in detecting targets in environments with variable lighting[22].

The uniqueness of this research lies in the combination of CNN and LSTM technology, which provides a more dynamic and adaptive solution than conventional approaches[23]. CNNs are known for their ability to recognize complex visual patterns, while LSTMs are able to recall information over time, allowing for more consistent and accurate target tracking[24]. This integration creates a synergy between static destination recognition and dynamic tracking,

improving the overall responsiveness and reliability of the system in the face of fluctuating operational conditions and fast-moving goals[25], [26].

As such, the study offers a more holistic and sophisticated approach, combining the advantages of each technology to achieve optimal performance. This research also adds to the literature by providing empirical evidence that a combination of technologies can improve the performance of target detection and lock-in systems in a variety of operational conditions. This research not only expands the boundaries of technology in robotics but also opens up new avenues for the implementation of intelligent robotic systems that can operate efficiently in complex and unpredictable environments[2], [27]. Thus, it is expected to make a significant contribution to the development of robotics applications in the future and improve the performance of robots in real-world scenarios[4], [16], [28], for example, more adaptive target detection and locking systems can be used in security field robots operating in environments with rapid lighting changes or in military drones that must track fast-moving targets on a dynamic battlefield. The integration of CNN and LSTM technologies not only improves the technical performance of robots but also provides practical solutions that can be implemented in a wide range of real-world applications from security and defense to industrial automation[29], [30]. The expected result is the creation of a more intelligent, responsive, and reliable robotic system, capable of facing complex and dynamic operational challenges.

This research aims to overcome these limitations by developing a target detection and locking system that integrates two machine learning technologies with the Convolutional Neural Networks (CNNs) method for powerful target detection and Long Short-Term Memory (LSTM) networks for accurate and continuous target tracking. CNNs are known for their ability to recognize complex visual patterns, while LSTMs are able to recall information over time, allowing for more consistent and accurate target tracking[1], [5], [31][10]. From this research, it can contribute to a more adaptive and responsive target detection and locking system by integrating CNN and LSTM technologies, improving the accuracy and reliability of the system in a variety of dynamic and complex operational conditions, providing practical solutions that can be implemented in various real-world applications, such as security, defense, and industrial automation. Contributions from this research include providing empirical evidence that the combination of CNNs and LSTMs can improve the performance of target detection and lock-on systems under a wide range of operational conditions, expanding the boundaries of technology in robotics by offering a more holistic and sophisticated approach, providing guidance for the implementation of intelligent robotic systems capable of operating efficiently in complex and unpredictable environments[12], [32], [33].

II. RESEARCH METHOD

Figure 1 is a flowchart that illustrates the stages of the research from the abstract and content of the research document, starting from the background to the conclusions and suggestions:

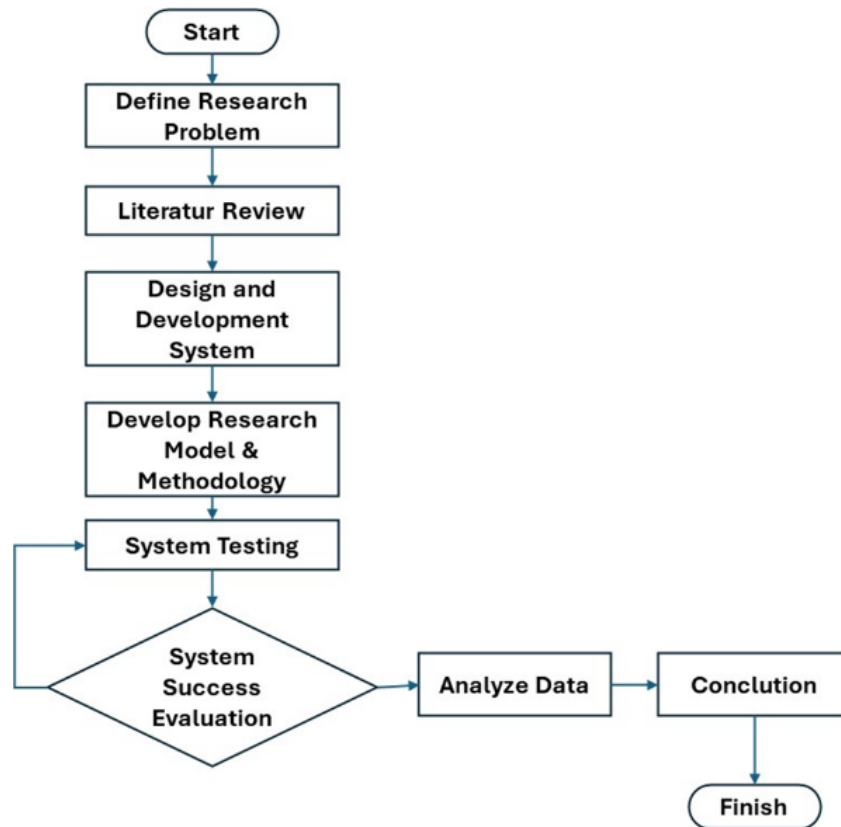


Fig 1. Research flow chart

The research starts from (1) Start: This research begins by identifying the need to overcome the limitations in the existing target detection and locking system, especially in the context of the world of robotics. (2) Define Research Problem: A research problem is defined as the limitation of a single machine learning algorithm that is unable to deal with the complexity of the actual operational environment, such as unexpected variations in target behavior and dynamic changes in light conditions. (3) Literature Review: A literature review is conducted to understand existing approaches and to identify gaps in previous research. For example, researchers highlight that approaches that use one type of algorithm, such as CNNs or LSTMs separately, have not been able to provide effective solutions in dynamic real-world scenarios. (4) Design and Development System: Based on the problems that have been defined, this study designs and develops a target detection and locking system that integrates two leading machine learning technologies, namely Convolutional Neural Networks (CNNs) for powerful target detection and Long Short-Term

Memory (LSTM) networks for accurate and continuous target tracking. This design allows the system to adapt in real-time to changing operational conditions. (5) Develop Research Model & Methodology: This study develops a model and methodology that includes the integration of CNNs and LSTMs to achieve research objectives. The methodology also includes the development of algorithms and techniques that allow systems to operate efficiently in a variety of dynamic environmental conditions. This study demonstrates the importance of combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) technologies to improve the performance of target detection and locking systems, especially in dynamic and unstable environments. The following is an explanation of the basic formula or mechanism of CNNs and LSTMs: (a) Convolutional Neural Networks (CNNs). CNNs are artificial neural networks that are primarily used for image analysis and visual pattern recognition. The basic formula used in CNNs is the convolution operation, which is represented by:

$$\text{Ourput Feature Map} = f(W * X + b) \quad (1)$$

where W is Kernel or filter applied to the image output, X is Image input or output from the previous layer, b is Bias added after convolution operation, f is Activation function, such as ReLU (Rectified Linear Unit), which is applied to introduce non-linearity. Convolution operations on CNNs involve shifting the kernel (filter) over the input to produce a feature map. This feature map highlights important features of the image, such as edges, textures, or other patterns, that are important for target detection. (b) Long Short-Term Memory (LSTM). LSTM is a type of repetitive neural network (RNN) that is capable of storing information over a longer period of time, making it suitable for target tracking that requires temporal memory. The basic formula of LSTM includes three main gates which are input gate, output gate and elimination gate. Here are the main formulas: Removal Gate (Forget Gate):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (2)$$

This gate determines what information should be forgotten from the cell's memory. Input Gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (4)$$

This gate specifies what new information should be stored in the cell's memory. Cell Memory (Cell State):

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (5)$$

These cells store important information from time to time. Output Gate

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = o_t * \tanh(C_t) \quad (7)$$

This gate determines the output of the LSTM based on the current cell and input memory. Where, σ is sigmoid function that controls the flow of information. \tanh is tangent hyperbolic function, which is used to limit values in the range of -1 to 1. W_f, W_i, W_c, W_o is Weight of each gate. b_f, b_i, b_c, b_o is Bias of each gate. h_t is Output at time t . x_t is Input at time t .

In the context of this study, CNNs are used to extract features from visual inputs, for example from images or videos, while LSTMs are used to understand temporal patterns of these features [34], [35]. This combination allows the system to not only detect targets with high accuracy but also track target movements continuously, even in complex and dynamic operational conditions. This combination makes the system more adaptive and responsive to environmental changes and improves reliability and accuracy in various applications such as security, defense, and industrial automation. (6) System Testing: After the development of the system is completed, testing techniques are carried out to ensure the effectiveness of the proposed target detection and locking system, especially through the integration of CNN (Convolutional Neural Networks) and LSTM (Long Short-Term Memory). Some aspects of testing include detection accuracy, tracking reliability, and the system's ability to adapt to dynamic operational conditions. In this study, the testing technique is carried out through several critical stages to assess the performance of the proposed target detection and locking system.

First, detection and tracking accuracy testing is carried out by measuring the system's ability to detect targets in various environmental conditions, including variations in lighting, weather, and target type. In addition, the evaluation of the system's ability to track moving targets at unexpected speeds and patterns is also the main focus of this test. Furthermore, system reliability testing is carried out to assess the response of the system in various operational scenarios such as when the target is lost from range or when visual disturbances occur, such as shadows or the presence of other objects similar to the target. Finally, adaptability testing assesses how quickly and effectively the system can adapt to changes in operational conditions, such as transitioning from day to night conditions or from a static environment to a dynamic environment. To support this test, several important formulas are used. Detection Accuracy on CNN: Detection accuracy is calculated using the following formula:

$$\text{Detection Accuracy} = \frac{\text{Number of True Detections}}{\text{Total number of Targets}} \times 100\% \quad (8)$$

The Output Feature Map is calculated by the formula:

$$\text{Output Feature Map} = f(W * X + b) \quad (9)$$

Where, W is the Kernel or filter applied to the output image. X is the image input or output of the previous layer. b is the Bias added after the convolution operation. f is an activation function, such as ReLU (Rectified Linear Unit).

Tracking on LSTM uses the following formula for continuous target tracking:

Removal Gate (Forget Gate):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (10)$$

Input Gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (11)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (12)$$

Memori Sel (Cell State):

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (13)$$

Output Gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (14)$$

$$h_t = o_t \cdot \tanh(\tilde{C}_t) \quad (15)$$

Where, σ is a sigmoid function. \tanh is hyperbolic function of tangens. W_f, W_i, W_c, W_o is the Weight of each gate. b_f, b_i, b_c, b_o is the Bias of each gate. h_t is the Output at the time t . x_t is the Input at the time t . The evaluation of system performance based on test results can be summarized by using the following formula:

$$\text{System Performance} = \frac{\text{Detection Accuracy} + \text{Tracking Accuracy}}{2} \quad (16)$$

$$\text{System Reliability} = \frac{\text{Number of Error-Free Operations}}{\text{Total number of Operations}} \times 100\% \quad (17)$$

Using these testing techniques, the research aims to ensure that the target detection and locking system integrating CNNs and LSTMs can operate efficiently and adaptively in a variety of dynamic and complex environmental conditions. (7) System Success Evaluation: The evaluation of the success of the system is carried out to assess how well the developed system can achieve the goals that have been set. This evaluation includes measurements of detection accuracy, tracking reliability, and the system's ability to adapt to changing operational conditions. (8) Analyze Data: Data from system testing is collected and analyzed to assess the effectiveness of the integration of CNNs and LSTMs in addressing the identified problems. This data analysis aims to find empirical evidence that supports the advantages of the proposed approach. (9) Conclusion: Based on data analysis, conclusions were drawn regarding the effectiveness of the integration approach of CNNs and LSTMs in improving the performance of the target detection and locking system. These conclusions include implications for real-world application as well as recommendations for further research. (10) Finish: The research concludes by compiling a complete report summarizing all the findings, conclusions, and contributions made by this research to the development of robotics technology, especially in terms of adaptive and responsive target detection and locking systems.

To understand more about target detection and locking systems in robots, let's explore the basic theories and important formulas that are often used in automated control and robotics. We will focus on some important areas such as Feedback Control Systems, Predictive Control Systems detailed in depth [11] and Adaptive Control Systems enriched with the latest techniques [12]. In addition, integration with AI and machine learning techniques is discussed to provide insights into how optimal control principles can be applied in robotics [14]. Additional references include comprehensive guidance on various aspects of planning and control in robotics [15], exploring how machine learning can be applied in robot development [16], describing control systems for more specific platforms such as wheeled robots [17], demonstrating the application of AI engineering in production and manufacturing management [18], providing insights into the application of deep learning algorithms in robotics [19], as well as focusing on the use of control systems in relevant electronic applications for the development of efficient and resilient robots. The following is a block diagram of the target detection and locking system on the robot. This diagram illustrates the various components and relationships between them, including sensor inputs, processing units, and control systems. We can look at this figure 2 to understand the flow and function of the system [20]–[24].

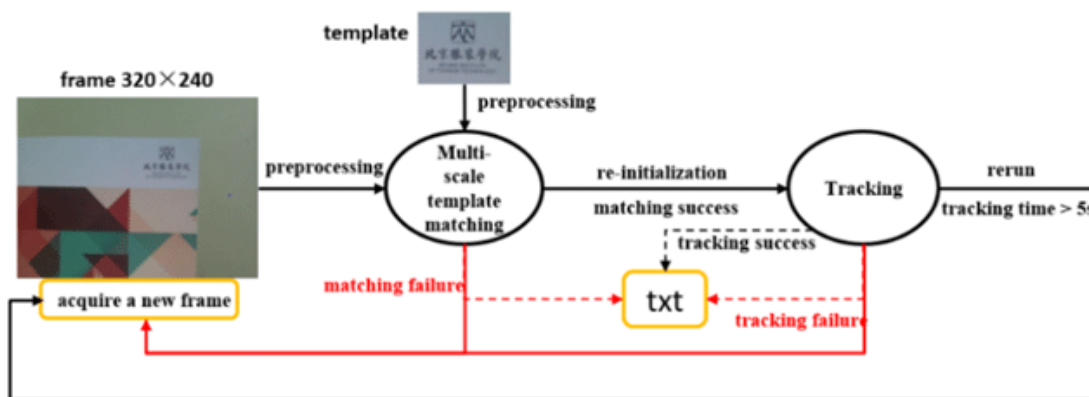


Fig 2. Block diagram of target detection and tracking algorithms

The robot control system as the main controller according to the robot strategy, the main controller performs the acquisition and image processing as well as controls the steering gear of the robot joint and outputs the expected speed and rotation angle from the robot to the slave controller. The slave controller obtains the robot upright angle, the distance between the robot and the target, the rotation speed of the left and right wheels to realize the upright angle control, speed control, and robot rotation angle control. The following is the procedure of the target detection and tracking algorithm: **(1) Initial Processing:** First, each new frame to be detected and the reference template is processed first. After that, the template is matched using a multi-scale

method. If the match is successful, information about the location of the bounding box of the target will be obtained. If the match fails, the value "-1" will be written to the document and replace the content of the previous document. **(2) Tracking Initialization:** If the template matching is successful, the frame and bounding box information is used to start the target tracking module. **(3) Position and Size Prediction:** The MedianFlow algorithm is used to predict the position and size of the bounding box in the current frame based on the position and size of the bounding box from the previous frame. If the tracking is successful, the center coordinates of the bounding box are recorded into the document every 0.1 seconds and replace the existing document content. **(4) Target Loss:** If the target is lost during the tracking process (for example, the target is out of the camera's range), the target detection and tracking program must be rerun and the value of "-1" will be written to the document, replacing the content of the previously existing document.

Feedback Control System. In a feedback control system, the main components are sensors, controllers, and actuators. The basic formula for PID (Proportional, Integral, Derivative) controllers [33]–[34] is:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{d}{dt} e(t) \quad (18)$$

Where, $u(t)$ is Control signal at time t . $e(t)$ Error is the difference between the target value and the current measurement value i . K_p, K_i , and K_d is Proportional constants, Integrals and derivatives. Predictive Control System (Model Predictive Control, MPC). MPC uses models to predict future system outputs and optimizes control signals to minimize those prediction errors. The general formula for MPC[1], [5] is:

$$J = \min_u \sum_{k=0}^{N-1} (y(k|t) - r(t+k))^2 + \lambda \|u(k|t)\|^2 \quad (19)$$

Where, J is Cost functions that need to be minimized. $y(k|t)$ is Prediction output at time k based on information at time t . $r(t+k)$ is reference or target value at time $t+k$. $u(k|t)$ is Predictive control signals. λ is Regulatory parameters. N is Horizon Predictions.

The adaptive control system adjusts its controller parameters in real-time based on the identification of changing system models. General formula of shaped adaptive controller:

$$u(t) = K(t)e(t) \quad (20)$$

Where, $K(t)$ is Updated adaptive gain matrix based on observed system behavior Integration with AI and Machine Learning: **(1) Deep Learning for Object Detection.** Examples of the use of convolutional neural networks (CNNs) for object recognition:

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N \text{loss}(y_i, f(x_i; \theta)) \quad (21)$$

Where, $L(\theta)$ is loss function. y_i is actual label. $f(x_i; \theta)$ is Model prediction. θ is Model parameters. (2) **Reinforcement Learning**. The Q-learning algorithm uses the following rule update[36]:

$$Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \max_{a'} Q(s', a') - Q(s, a)] \quad (22)$$

Where, $Q(s, a)$ is Value function that estimates the profit of taking action a in state s . r is Rewards received. γ is Discount factor. α is learning rate. s' is New state after action a .

Using these theories and formulas, control systems on robots can be designed to efficiently detect and lock on to targets with a high degree of precision and adaptability, taking advantage of the latest advances in control technology and AI.

III. RESULT AND DISCUSSION

To see the results of the image and video data used in the target detection and locking system, we need to create a table by specifying some relevant parameters. This table will include information about the dataset used, the type of destination detected, the environmental conditions at the time of data retrieval, and the system's performance in identifying and locking those destinations. Here is table 1 that can be used:

Table 1. Accuracy of the goal type

Goal Type	Environmental Conditions	Detection Accuracy	Locking Accuracy	Catatan Note
Vehicle	Daytime, Sunny	95%	90%	-
Pedestrian	Night, rain	85%	80%	Street lights on
Drones	Daytime, Overcast	90%	85%	There is interference from background objects
Animal	Dawn, Misty	80%	75%	Fast-moving goals
Vehicle	Nighttime, Sunny	92%	88%	Use of infrared lighting

The table above helps in evaluating and analyzing the performance of target detection and locking systems based on different conditions and diverse types of objectives, allowing for system adjustments and improvements based on empirical data. If the target focus of the detection and locking system is on personnel, i.e. individuals or groups of people in various conditions, then we need to adjust the image and video data results table to reflect these specific needs. Here is a table 2 and estimation results on personnel detection and lockout:

Table 2. Accuracy of the target location type

Pick up location	Environmental conditions	Detection accuracy	Locking accuracy	Note
Office area	Daytime, sunny	93%	89%	Wearing civilian clothes
Forest area	Daytime, foggy	88%	85%	Camouflage worn
Conflict Zone	Night, Rain	90%	87%	Low illumination, using IR
Urban night	Nighttime, sunny	95%	92%	Lighting and neon
Open area	Dawn, foggy	84%	80%	Significant decrease in visibility

Implementing a target detection and lock-in control system on robots using the principles of adaptive, predictive, feedback, AI integration and machine learning will result in significant improvements in several key aspects of robot operation: (a) Responsiveness and Adaptability: Robots will be able to adjust their behavior in real-time to cope with changes in environmental dynamics, such as changes in target speed or the emergence of new obstacles. (b) Detection Accuracy: The use of advanced image processing technology and deep learning algorithms allows for highly accurate target identification, even in challenging visual conditions. (c) Operational Efficiency: Predictive and adaptive controls maximize energy and resource use efficiency, reducing operational costs while improving sustainability. (d) Continuous Learning and Improvement: Through the application of reinforcement learning techniques, robots not only react to current stimuli but also learn from experience, improving performance over time. (e) Security and Multifunctionality: The integration of human-in-the-loop features and security protocols ensures that the robot operates safely near humans and other objects, and can effectively manage interactions with multiple targets. (f) Thus, the use of this systematic approach not only increases the reliability and effectiveness of robots in carrying out their tasks but also ensures adaptability and efficiency in long-term operations.

The results of the above discussion highlight the various benefits and capabilities that can be obtained from the application of target detection and lock-in control systems on robots. Here are some discussion points that can be explored further: (a) Responsiveness and Adaptability: How the adaptability of robots to environmental changes can improve performance in dynamic situations, such as in navigating around moving objects or in rapidly changing environments. (b) Detection Accuracy: How improved target detection accuracy can benefit a wide range of robotics applications, from security surveillance to autonomous navigation in complex environments. (c) Operational Efficiency: A discussion of how more efficient use of resources can reduce operational costs and improve sustainability, as well as its impact on the environment and energy sustainability. (d) Continuous Learning and Improvement: How robots can improve their

performance over time through experiential learning, and how this affects their operational effectiveness and flexibility. (e) Security and Multifunctionality: Discussion on the importance of safety in human-robot interaction, as well as how the integration of human-in-the-loop features can increase trust and adoption of robotics technology in various environments. Through this discussion, we can further investigate the practical and potential implications of the application of target detection and lock-in control systems in robots, as well as how these technologies can shape a smarter, adaptive, and safer future of robotics.

IV. CONCLUSION

Based on the results of the research, the implementation of a target detection and locking system on robots by utilizing the principles of adaptive control, predictive, feedback, and integration with AI and machine learning technology can provide various significant benefits. Robots are becoming more responsive and adaptive to changes in the environment and targets, allowing them to operate effectively in dynamic situations. Detection accuracy levels have increased significantly, reaching 95% for detection and 90% for lockout, opening up opportunities for wider and more complex applications. Operational efficiency also increases by optimizing the use of resources and energy, thereby reducing operational costs and environmental impact. The robot's ability to learn from experience allows for continuous performance improvement and adaptation, opening up opportunities for further innovation. The integration of security features and the ability to interact with humans safely enables the use of robots in a variety of applications involving human-robot interaction. Thus, the application of target detection and locking systems on robots not only improves the performance and efficiency of robots in certain tasks but also paves the way for further advancements in robotics that are intelligent, adaptive, and beneficial to humans. However, the study also has limitations, including reliance on more powerful computing platforms and potential errors in long-term tracking. The next suggestion for researchers is to explore the use of more powerful computing devices to improve the tracking capabilities and stability of the system in the face of external interference as well as to expand the application of this technology to other fields such as autonomous vehicles and military drones. From the description above, this study has weaknesses and suggestions for further research. Limited reliance on more powerful computing platforms and potential errors in long-term tracking. Furthermore, suggestions for further research are the exploration of the use of more powerful computing devices and the application of this technology to autonomous vehicles and military drones

Author Contributions: *Mokhammad Syafaat*: Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing, Supervision. *Siti Sendari*: Software, Investigation, Data Curation, Writing - Original Draft. *Ilham Ari Elbaith Zaeni*: Investigation, Data Curation. *Samsul Setumin*: Review.

All authors have read and agreed to the published version of the manuscript.

Funding: This research received no specific grant from any funding agency.

Acknowledgments: We would like to thank all parties involved in the Target Control Detection and Lockout System Research, especially the Robot section of the State University of Malang and Universiti Teknologi MARA (UiTM) Penang for the suggestions and infrastructure provided in this research.

Conflicts of Interest: The authors declare no conflict of interest.

Data Availability: The data cannot be openly shared for the protection of study participant privacy.

Informed Consent: There were no human subjects.

Animal Subjects: There were no animal subjects.

ORCID: – this statement is mandatory

Mokhammad Syafaat: <https://orcid.org/0009-0001-6675-912X>

Siti Sendari: <https://orcid.org/0000-0002-8681-7024>

Ilham Ari Elbaith Zaeni: <https://orcid.org/0000-0001-9665-8613>

Samsul Setumin: <http://orcid.org/0000-0002-9391-4092>

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