DUAL-STAGE IDENTIFYING DATA OF ARM ROBOT FOR RECOGNIZING AND SORTING OBJECTS WITH DOUBLE FACES PERMITTED-PROHIBITED AREA

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ABSTRACT: When relocating objects to specific directions, sometimes a particular object is surrounded by another object with directions, such as a permitted-prohibited area. The arm robot functions are to identify objects in the workspace and detect permitted or prohibited areas. Then, the arm robot should be able to recognize how many objects to be relocated. In addition, the arm robot also identifies permitted-prohibited locations. In this study, a dual-stage arm robot method for object recognition and sorting with permitted/prohibited zones was examined. Furthermore, the dual-stage method was evaluated under experimental conditions, where several objects, represented by pawns, pictures of snakes, and ladders, were placed in a workspace. The first stage was to identify each object in the workspace, and the second stage identify whether there were any permitted-prohibited areas.

The proposed method was evaluated by comparing the accuracy, precision, recall, and f1-score of dual-stage and single-stage methods. The results showed that the accuracy, precision, recall, and F1-score of identifying objects increased to 99.47%, 98.73%, 95.45%, and 96.86%, respectively. Then, determining the start of grabbing location and relocating the pawn to the new location were achieved successfully.

KEYWORDS: *Arm robot; dual-stage method; identifying data; object recognition; object movements*

1.0 INTRODUCTION

Arm robots, which mimic human arm functions, are frequently utilized to help people carry objects and complete repetitive jobs like choosing and positioning objects that require high accuracy [1]. Numerous arm robots have recently been created to sort goods and arrange items on shelves [2]. Then, selecting objects effectively and relocating objects precisely are very essential. Here, accurate object position estimation is crucial for successfully picking an object.

Since arm robots are widely utilized in industrial applications, it is crucial to introduce them in technical schools as teaching tools. However, they are unsuitable for widespread education because of their expensive cost and closed source, among other factors. In the field of education, commercial robotic arms currently make up the majority. Numerous robotics curricula have undergone revisions, in which some courses are introduced via the project-based learning methodology [3], challenge-based learning methodology [4], [5], and interactive learning environment [6], [7]. Using instructional robotic arms leads to improved communication, higher motivation, and growth of transversal abilities [6].

Since 2000, progress has been made in the development of arm robot educational kits, or "edu-kits." These edu-kits often introduce essential hardware components, like microcontrollers, motors, sensors, and simple programming steps [8], [9]. The development of edu-kits has been extended, allowing users to use them without extensive technical knowledge. They can be applied as a tutor, teaching, or learning tool. The essential characteristics of the developing edu-kits are that components of the edu-kits should be easily connected and disconnected components [10]. At the same time, the programming interfaces should be more intuitive and accomplished with graphical programming languages to facilitate learning [11],[12].

This paper described how to accomplish several projects using the edu-kits robotic arm and associated devices. It also discussed how to operate the robotic arm to respond appropriately to changing circumstances in the work area, such as deciding which object to pick up and relocating it to the right spots when any other objects surrounding the object have specific directions to follow. Under such circumstances, the arm robot ought to be able to recognize the targeted objects and locations in terms of pawns, ladders, snakes, and dice that influence the arm robot's motions [13]. Currently, a camera sensor is a vital instrument for capturing visual data [14], and it is frequently applied in vision-based object recognition [15], [16]. As a result, the arm robot and vision sensor work together to detect and locate objects accurately. This process needs a sequential process of reading, interpreting, and being sent through the path planning and trajectory generation modules [17]. Furthermore, the computation involved in the learning process is challenging since it utilizes sophisticated hardware and unique algorithms, such as artificial intelligence and classification systems [18], [19]. Then, the arm robot ought to be able to identify the targeted objects and positions in terms of pawns, ladders, snakes, and dice that influence the arm robot's motions [13], [20]

Generally, complex objects are to be identified based on their different discriminators, such as adding a local identifying [21] or achieving optimal results in precision, recall, and F1-score [22]. At the same time, two-stage method is mainly used for cases with large-size data and categorical or binary-valued uncertain data [23]. Furthermore, when the identified object determines a location that can be permitted or prohibited for visiting, a graph representation is modelled, such as strict preferences [24] or identifying forbidden subgraphs [25].

This study was to determine arm robot movements to sort and recognize objects with double faces in permitted-prohibited areas, such as selecting the upper or bottom part of ladders. This work used an arm robot's grasping and positioning method by simulating pawns and pictures of snakes and ladders [13], [20]. Here, the arm robot could recognize items in the work environment and distinguish between places that were allowed and those that were not. The arm robot then could recognize the number of pawns that needed to be moved. The arm robot additionally could recognize the top and bottom of staircases as well as the permissible and prohibited areas denoted by the heads and tails of snakes. Ultimately, the F1-score, accuracy, precision, and recall of the identification findings were assessed.

2.0 METHODOLOGY

The arm robot was developed to sort and recognize pawns, snake pictures, and ladder pictures, as shown in Figure 1. The system consisted of (1) a camera sensor to identify the workspace, (2) colored pawns representing sequences of objects to be relocated, (3) snakes' and ladders' objects on the board representing rules, (4) a board as the workspace, (5) an arm robot to handle the pawns in the workspace, and (6) a programming interface.

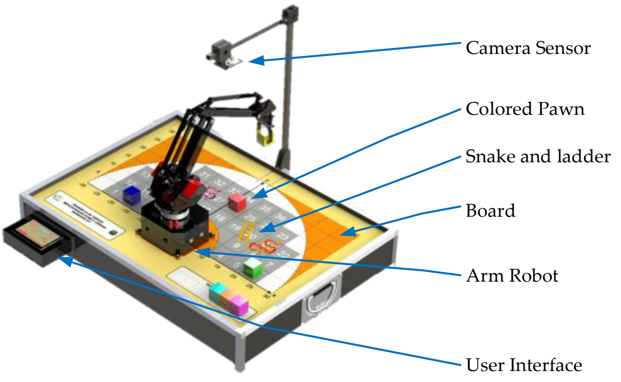


Figure 1: The proposed arm robot for identifying and sorting objects

The arm robot had 4 DOFs, i.e., the base, shoulder, elbow, and wrist. The elbow link measured 160 mm, whereas the shoulder link measured 148 mm. The arm's operational range was between 300 and 80 mm. A gripper was attached as the end-effector of the arm robot for picking up the pawns. Using the x, y, and z coordinates, the arm robot might move over to the 3D work area. The arm robot movements were achieved through the base joint's rotating 180 degrees horizontally. The design of the arm robot is shown in Figure 2.

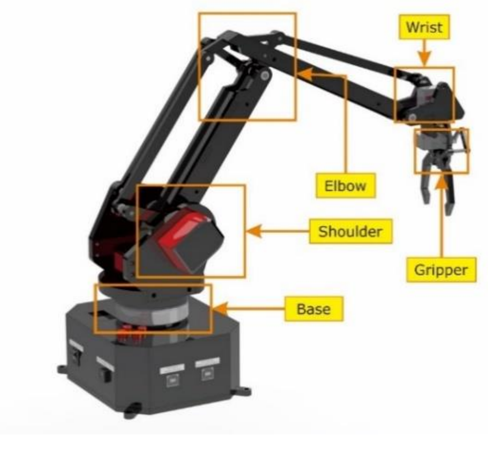


Figure 2: The designed arm robot

2.1 Workspace of Experimental Conditions

The workspace of the experimental condition was a board within 500 x 700 mm. A camera was installed at a fixed position, capturing the area of the board as the workspace. The workspace was divided into several numbering grids used to identify objects like pawns, snakes, and ladder positions. Then, Yolo’s approach was to be applied to identify objects. The arm robot was set to reach pawns on the workspace within 180 degrees. The pawns were colored cubes with 40 x 40 x 40 mm dimensions, which should be relocated to locations by identifying objects indicated with double faces in permitted-prohibited areas.

Procedures to identify the game board are as follows. (1) First, the camera captured the board and changed into HSV; (2) the processor selected the active area and determined calibration points; (3) the active area was divided into several grids, as shown in Figure 3, and (4) the grids were numbered from 1 to 36 (Grid_ID) based workspace as shown in Figure 3.

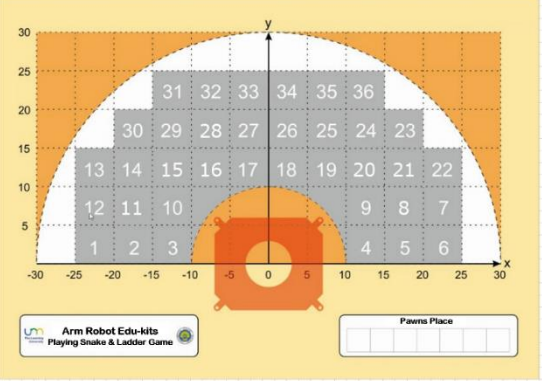


Figure 3: Game board of arm robot

2.2 Movement of Arm Robot

The arm robot movements were designed to relocate pawns using sequence steps as follows: (1) the camera sensor was calibrated to determine the specific workspace area [16], [18]; (2) the camera was trained by using Yolo’s algorithm to identify several objects, such as ladders, and four different colored pawns, i.e., red, green, blue, and yellow [26], [27]; (3) the information of camera was processed to generate pawns’ color id, recent position, and target position; (4) the pawns' positions were transformed to the real-world coordinates via the pixel position regression method; (5) According to the dice’s number, snakes and ladders' position, the arm robot chose appropriate movements of the gripper to grasp pawns and relocated them to target positions.

2.3 Dual Stages Identifying Data of Arm Robot in Sorting and Recognizing

Objects were identified by using Yolo's algorithms with dual-stage identification. The camera identified pawns, snakes, and ladders. In the first stage, the camera identified the kind of objects; in the second stage, it provided the position of the head or tail of snake pictures and that of top or bottom ladder pictures. These positions were saved as the reference of the arm robot to move the pawns according to the number of dice and position of snakes and ladders.

The center positions (x, y) and sizes (width, height) of the identified objects inside the covered workspace area were represented by the camera data to be delivered to the processor. Then, these coordinates were transformed into the angle values of the arm robot's join actuators.

This paper proposed a dual-stage method of identifying data during movement since it was needed to determine a more specific part of objects. Dual-stage is mainly implemented in cascade controller [28], [29] or exploration and exploitation for constrained multiobjective optimization [30]. The general architecture of the dual-stage method has been introduced by Yao, et.al. [22]. The first stage identified different objects, whereas the second stage implemented a learning process to determine the snakes' heads and tails and the ladders' top and bottom. After identifying data, the process was continued to define the pawns' ID, recent position, and target position. The mechanism of the dual-stage method of identifying data is shown in Figure 4.

The advantage of this proposed method was to identify permitted and prohibited locations, shown by a figure; for example, instead of just identifying the location of a snake picture, the proposed method could identify the location of the permitted and prohibited locations shown by the head and tail of the snake picture.

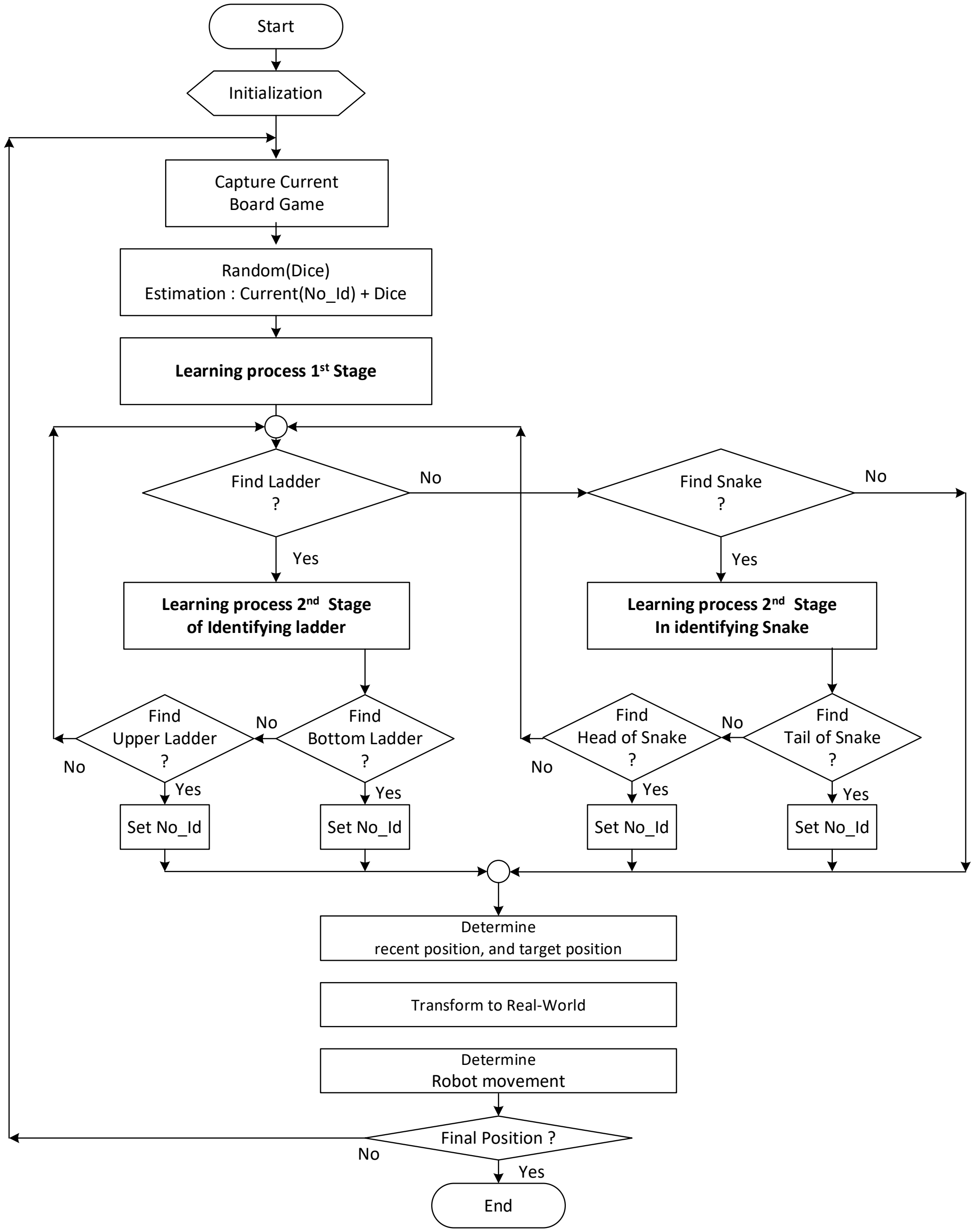


Figure 4: Sorting rule for the case study

3.0 RESULTS AND DISCUSSION

During the experiment process for relocating pawns, testing the arm robot with dual-stage identifying data could affect the movement's rule when other objects surrounded pawns. The initial phase was to assess the efficacy of object position recognition by using Yolo's algorithm to estimate the actual positions of the pawns, ladders, and snakes in the workspace. Then, two experimental procedures were implemented as follows.

3.1 Sorting and Object Recognition

In the first stage, the experiment evaluated the efficacy of the pixel position regression method in interpreting objects, such as pawns, snakes, and ladders, on the game board using input from the camera sensor. These objects were placed on the board and detected to interpret their kind and number position in related grids. A grid is partitioned with an interval of 5 cm, as seen in Figure 3.

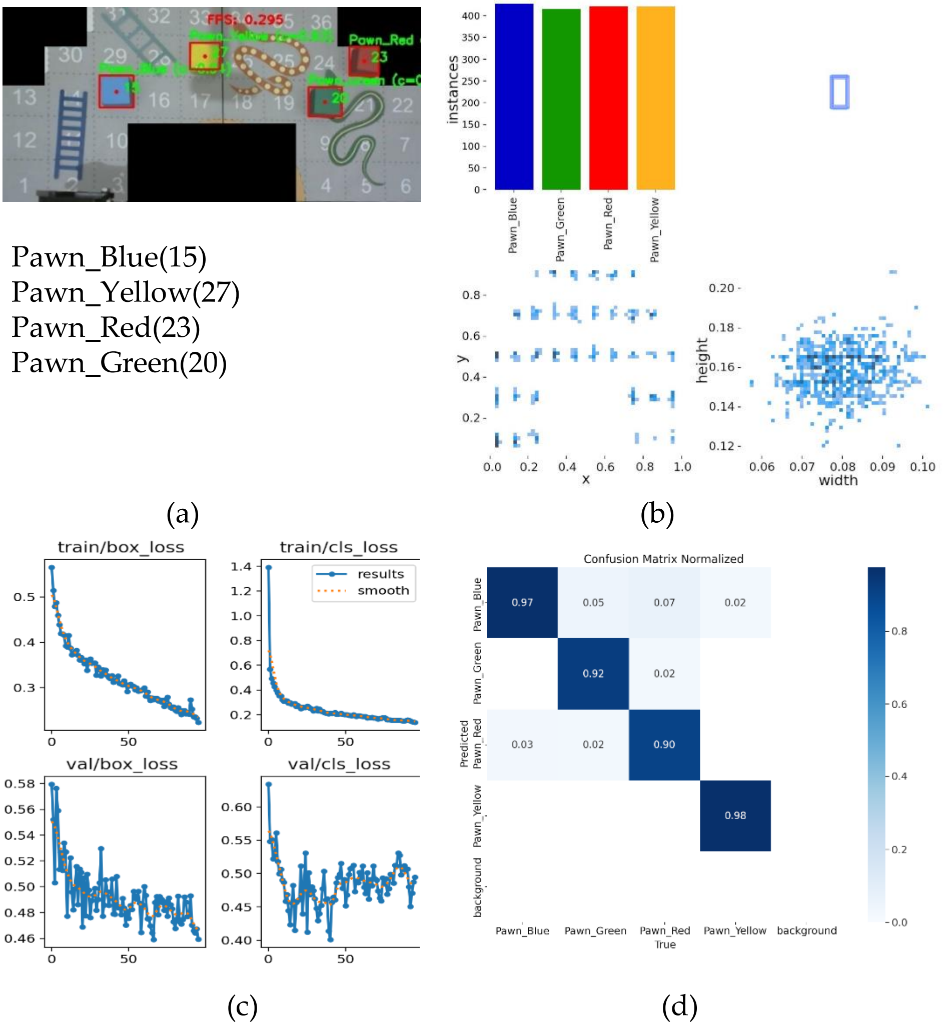


Figure 5: Identification of pawns in the workspace; (a) Pawns' object detection; (b) pawns' instance; (c) training and validation results; and (d) Normalized cross-validation results

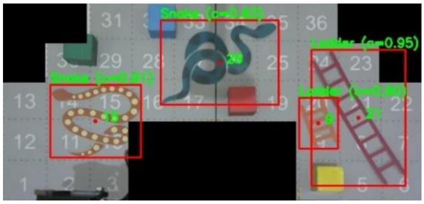
First, calibration was done using pawns' identification. Pawns were identified as the location using pixel position regression. After Calibration, experimental conditions were set as follows: (1) the number of grids on the game board were 36, (2) the number of image data set training for pawns were 420, whereas validation and testing data were 40 and 20 respectively; and (3) the number of image data set for snakes and ladders were 633, whereas validation and testing data were 50 and 20 respectively.

The training process for identifying pawns is shown in Figure 5. Figure 5(a) illustrates the identification of pawns, demonstrating the successful identification of pawns by color. The configurations of how the pawns were placed on the game board are shown in Figure 5(b). Using 100 epochs, the training and validation results showed that the number of unidentified pawns (box_loss) and unidentified colors of pawns (cls_loss) decreased in the final epoch, as shown in Figure 5(c). It is also confirmed through the confusion matrix shown in Figure 5(d). The pawns' identification possessed accuracy, precision, recall, and f1-score, as shown in Table 4. The architecture of pawns' identification can be compared to coarse-stage classification [22]. The results of pawn identification show an average above 94.36%.

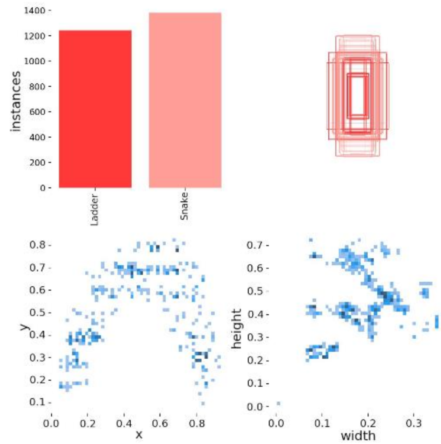
To improve the accuracy, the training process for identifying ladders and snakes could be enhanced using two stages [31], [22]. The proposed dual-stage method was to identify the permitted-prohibited area. The first stage was applied to train for identifying specific areas, representing the class of snakes or ladders. The second stage was applied to identify permitted-prohibited areas. The permitted-prohibited areas were represented as the bottom-top of ladders or the head-tail of snakes. Figure 6 shows the first stage, whereas Figure 7 shows the second stage of identifying permitted-prohibited areas.

Table 4: Pawns identification accuracy, precision, recall and f1-score

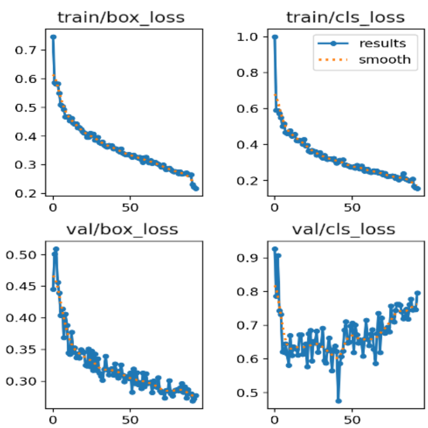
Class	Accuracy	Precision	Recall	F1-Score
Pawn_Blue	95.62%	97.29%	85.71%	91.13%
Pawn_Green	97.50%	92.50%	97.36%	94.87%
Pawn_Red	96.25%	90.47%	95.00%	92.68%
Pawn_Yellow	99.37%	97.56%	100.00%	98.76%
Average	97.19%	94.45%	94.52%	94.36%

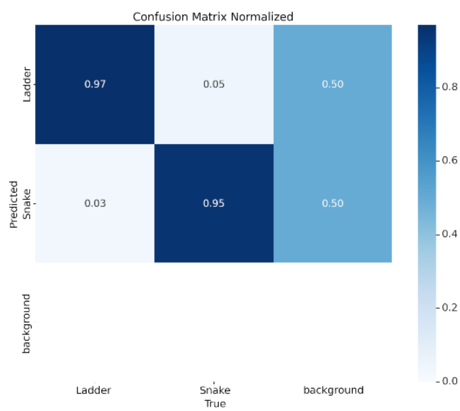


1st stage
Snake(15)
Snake(26)
Ladder(9)
Ladder(21)



(a) (b)





(c) (d)

Figure 6: Identification of objects for identifying specific areas in the workspace; (a) permitted-prohibited object detection; (b) permitted-prohibited instance; (c) training and validation results; and (d) Normalized cross-validation results

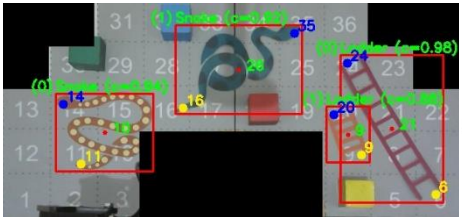
In the first stage, Figure 6(a) shows the identification results of specific areas represented by ladders and snakes. The configurations of how the snakes or ladders were placed on the workspace are shown in Figure 6(b). The training and validation results were shown as the number of unidentified boxes (box_loss) and class (cls_loss) of specific areas represented by snakes and ladders. Using 100 epochs, it decreased in the final epoch, as shown in Figure 6(c). It was also verified by using normalized cross-validation, as shown in Figure 6(d). The results of the first stage are shown in Table 5. The identification of the first stage reveals almost 94%, which is comparable to the Pawns identification findings displayed in Table 4.

Table 5: Ladder and Snake single-stage identification accuracy, precision, recall, and f1-score

Class	Accuracy	Precision	Recall	F1-Score
Ladder	94.93%	97.08%	92.59%	94.78%
Snake	94.93%	95.37%	94.49%	94.93%
average	94.93%	96.23%	93.54%	94.86%

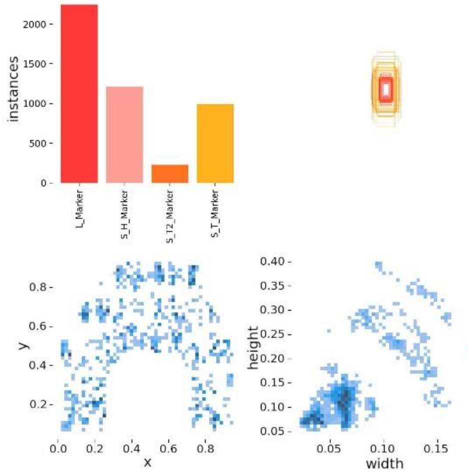
To find the target location in the workspace, the second stage of identifying the permitted-prohibited area was conducted by continuing to train objects. As the permitted-prohibited areas were represented as snakes and ladders, then, the training process was done as follows. Snakes were trained by identifying the head and tail, whereas ladders by identifying the top and bottom parts. While the identification results in the second stage are shown in Figure 7, the performances' are shown in Table 6.

The average scores for accuracy, precision, recall, and F1-score for object recognition in the second stage of identifying permitted-prohibited zones were 99.47%, 98.73%, 95.45%, and 96.86%, respectively. Next, it could achieve higher than 95% above the first stage and achieve 4.36% improvement in accuracy, 2.5% increase in precision, 1.91% increase in recall, and 2.69% rise in F1-score.

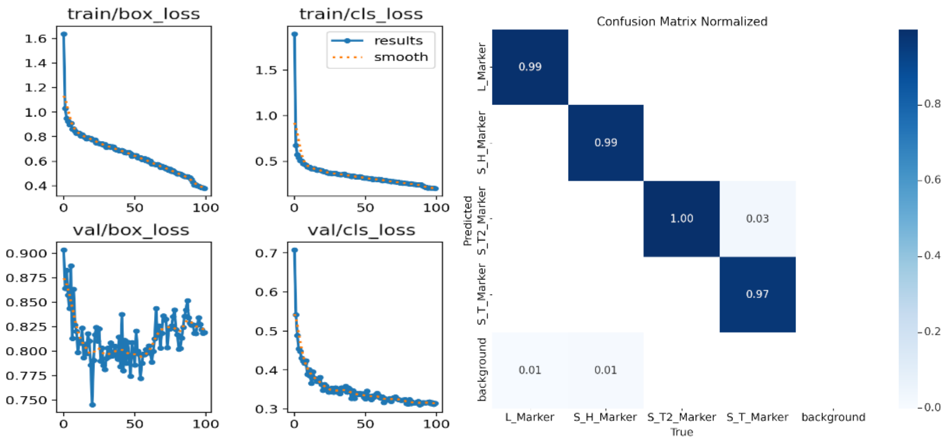


2nd stage

Snake(26), Head(35), Tail (16)
Snake(10), Head(14), Tail(11)
Ladder(21), Top(26), Bottom(6)
Ladder(9), Top(20), Bottom(9)



(a) (b)



(c) (d)

Figure 7: Identification of permitted-prohibited areas; (a) permitted-prohibited of object detection; (b) permitted-prohibited instance; and (c) training and validation results; (d) Normalized cross-validation results

Table 6: Ladder and Snake dual-stage identification accuracy, precision, recall, and f1-score

Class	Accuracy	Precision	Recall	F1-Score
L_Marker	99.64%	99.24%	100%	99.61%
S_H__Marker	99.64%	98.68%	100%	99.33%
S_T2_Marker	99.29%	100.00%	81.81%	90.00%
S_T_Marker	99.29%	97.01%	100%	98.48%
Average	99.47%	98.73%	95.45%	96.86%

3.2 Arm Robot's Performance in Relocating Object

During the experiment, pawns, ladders, and snakes were relocated to the workspace according to rule play. One executing time was determined as a range time when the robotic arm acted to grasp and raise the object, subsequently moving the robot to a certain place, as determined by the identification of the object.

Table 7 presents the effectiveness of the arm robot in relocating a pawn to an appropriate target. In the previous research, the arm robot successfully used an inverse kinematic method to determine the angle of the arm robot joints for grasping and repositioning objects [13]. However, the method of repositioning was determined according to the coordinates given by the user. In this paper, a camera was used to recognize the coordinates and provided the user with information.. Then, with dual-stage recognition, there was a 100% success rate in completing the pawn sorting and moving them to the targeted location. Figure 9 illustrates the exact movements of the robotic arm as it effectively seizes and moves a pawn from its original position to a target location. The findings have verified that the robotic arm can sort and recognize objects to perform diverse tasks, including grabbing, picking, and relocating objects.

Table 7: Completion task using dual stages identifying data

Task	Pawn	Start	Goal	Results
1	Green	1	3	Complete
2	Yellow	1	4	Complete
3	Red	8	13	Complete
4	Blue	24	29	Complete

(a) (b) (c)

Figure 9: Example of the pawn movement when the robot relocating it from a starting point to the new location on the workspace

4.0 CONCLUSION

This work uses the dual-stage method of identifying objects to sort and recognize them. The proposed method could increase identifying objects to 99.47%, 98.73%, 95.45%, and 96.86% for accuracy, precision, recall, and F1-score, respectively. Using the proposed method, the experimental results show that the dual-stage can improve the performance above 95%. Indeed, the identification process has been successfully applied to the arm robot to move objects in the workspace. The movement of relocating objects is conducted by determining the start of grabbing location and relocating the pawn 100% to the new location. Dual-stage identification is used as an edu-kit for upcoming work, which makes use of the arm robot by figuring out data protocol to make the sorting and moving of objects program simpler. This method would be studied by observing users' viewpoints.

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AUTHOR CONTRIBUTIONS

Individual contributions of authors should be specified in this section to give appropriate credit to each author:

S. Sendari: Original Draft Preparation; Y. Rahmawati: Data Review; H. Rahmawati: Data Evaluation; Tibyani : Data Curation, I. A. E. Zaeni1: Validation; N. Khoirurizka : Software Application; M.A.F. Shodiq: Software Integration; D.A. Wibowo: Motion Mechanism; N. B. Mokhtar: Supervision; H. Lin: Writing-Reviewing.

CONFLICTS OF INTEREST

The manuscript has not been published elsewhere and is not being considered by other journals. All authors have approved the review, agree with its submission, and declare no conflict of interest in the manuscript.

REFERENCES

[1] S. Jotawar, M. Soni, and S. Kumar, "Motion Planning for an Automated Pick and Place Robot in a Retail Warehouse", in *Proceedings of the Advances in Robotics*, 2017, pp. 1–6.

[2] Y. Jaghbeer, R. Hanson, and M. I. Johansson, "Automated order picking systems and the links between design and performance: a systematic literature review", *International Journal of Production Research,* vol. 58, pp. 4489–4505, 2020.

[3] D. J. Cappelleri and N. Vitoroulis, "The Robotic Decathlon: Project-Based Learning Labs and Curriculum Design for an Introductory Robotics Course", *IEEE Transaction. on Education*, vol. 56, no. 1, pp. 73–81, Feb. 2013.

[4] R. E. Patiño-Escarcina, D. Barrios-Aranibar, L. S. Bernedo-Flores, P. J. Alsina, and L. M. G. Gonçalves, "A Methodological Approach to the Learning of Robotics with EDUROSC-Kids," *Journal of Intelligent and Robotic Systems: Theory and Applications*, vol. 102, no. 2, pp. 1-23, 2021.

[5] A. Syawaluddin, S. Afriani Rachman, and Khaerunnisa, "Developing Snake Ladder Game Learning Media to Increase Students' Interest and Learning Outcomes on Social Studies in Elementary School", *Simulation & Gaming*, vol. 51, no. 4, pp. 432–442, Aug. 2020.

[6] C. Zeng, H. Zhou, W. Ye, and X. Gu, "iArm: Design an Educational Robotic Arm Kit for Inspiring Students' Computational Thinking", *Sensors*, vol. 22, no. 8, 2022.

[7] M. Chetouan, V. Dignum, P. Lukowicz, and C. Sierra, *Human-Centered Artificial Intelligence*, vol. 13500. in Lecture Notes in Computer Science, vol. 13500. Cham: Springer International Publishing, 2023.

[8] S. E. Jung and E. S. Won, "Systematic review of research trends in robotics education for young children", *Sustainability*, vol. 10, no. 4, pp. 1-24, 2018.

[9] S. T. Chu, G. J. Hwang, and Y. F. Tu, "Artificial intelligence-based robots in education: A systematic review of selected SSCI publications", *Computers and Education: Artificial Intelligence*, vol. 3, pp. 1-9, 2022.

[10] K. Kadota, "Development of communication robot for STEM education by using digital fabrication," *Journal of Robotics and*

Mechatronics, vol. 29, no. 6. pp. 944–951, 2017.

[11] E. Petraki and D. Herath, "Teaching and Learning Robotics: A Pedagogical Perspective", in *Foundations of Robotics A Multidisciplinary Approach with Python and ROS,* D. Herath and D. St-Onge Eds. Singapore: Springer Nature Singapore Pte Ltd, 2022, pp. 43-62.

[12] M. Meng, S. Steinhardt, and A. Schubert, "Application Programming Interface Documentation: What Do Software Developers Want?", *Journal of Technical Writing and Communication*, vol. 48, no. 3, pp. 295–330, 2017.

[13] S. Sendari, Y. R. Wahyudi, I. A. E. Zaeni, A. N. Handayani, M. Muladi, N. Wicaksono, M. A. Fatwaddin, H. S. Lin, "Grasping and Repositioning Objects using Inverse Kinematic Method for Arm Robot based on Pixel Position Regression", *Journal of Advanced Manufacturing Technology*, vol. 16, no. 3, pp. 1985–3157, 2022.

[14] L. E. van Dyck, R. Kwitt, S. J. Denzler, and W. R. Gruber, "Comparing Object Recognition in Humans and Deep Convolutional Neural Networks—An Eye Tracking Study", *Frontiers in Neuroscience*, vol. 15, pp. 1-15, 2021.

[15] R. Jafri, S. A. Ali, H. R. Arabnia, and S. Fatima, "Computer vision-based object recognition for the visually impaired in an indoors environment: a survey", *Visual Computer*, vol. 30, no. 11, pp. 1197–1222, 2014.

[16] S. Sendari, D. Lestari, C. U. Kusumohadi, F. S. Wibowo, and K. Anam, "Integrating embedded color vision to Bioloid robot for playing soccer," in *2017 International Conference on Signals and Systems*, 2017, pp. 297–302

[17] P. Bilancia, J. Schmidt, R. Raffaeli, M. Peruzzini, and M. Pellicciari, "An Overview of Industrial Robots Control and Programming Approaches", *Applied Sciences (Switzerland)*, vol. 13, no. 4, pp. 1-14, 2023.

[18] M. F. Ahmad, S. S. N. Alhady, W. Rahiman, W. Othman, and A. A. M. Zahir, "RGB classification determination with different light intensity using Pixy CMUcam5," in *Intelligent Manufacturing & Mechatronics*, M.H. Arif Hassan, Pahang, 2018, pp. 517–525.

[19] H. P. Hariyadi, T. Widiyaningtyas, M. Z. Arifin, and S. Sendari, "Implementation of Genetic Algorithm to academic scheduling system," in *IEEE Region 10 Annual International Conference,*

Proceedings/TENCON, Penang, 2017, pp. 2013-2016.

[20] A. R. Al Tahtawi, M. Agni, and T. D. Hendrawati, "Small-scale robot arm design with pick and place mission based on inverse kinematics", *Journal of Robotics and Control*, vol. 2, no. 6, pp. 469–475, 2021.

[21] J. Subash and S. Kalaivani, "Dual-stage classification for lung cancer detection and staging using hybrid deep learning techniques", *Neural Computing & Application*, vol. 36, no. 14, pp. 8141–8161, 2024.

[22] Y. Yao, X. Wang, G. Zhou, and Q. Wang, "A two-stage substation equipment classification method based on dual-scale attention", *IET Image Process*, pp. 1-10, 2024.

[23] A. Subramanyam, "A Lagrangian dual method for two-stage robust optimization with binary uncertainties", *Optimization and Engineering*, vol. 23, no. 4, pp. 1831–1871, 2022.

[24] S. Huang and M. Xiao, "Object reachability via swaps under strict and weak preferences", *Autonomous Agents and Multi-Agent Systems*, vol. 34, no. 2, Oct. 2020.

[25] P. A. Golovach, D. Paulusma, and B. Ries, "Coloring graphs characterized by a forbidden subgraph", *Discrete Applied Mathematics*, vol. 180, no. C, pp. 101–110, 2015.

[26] T. Diwan, G. Anirudh, and J. V. Tembhurne, "Object detection using YOLO: challenges, architectural successors, datasets and applications", *Multimedia Tools and Applications*, vol. 82, no. 6, pp. 9243–9275, Mar. 2023.

[27] M.H.F.M. Fauadi, S. Akmal, M.M. Ali, N.I. Anuar, S. Ramlan, A.Z.M. Noor and N. Awang, "Intelligent vision-based navigation system for mobile robot: A technological review", *Periodicals of Engineering and Natural Sciences*, vol. 6, no. 2, pp.47-57, 2018.

[28] Y. Yang, W. Luo, and X. Tian, "Hybrid two-stage cascade for instance segmentation of overlapping objects", *Pattern Analysis and Applications*, vol. 26, no. 3, pp. 957–967, 2023.

[29] F. M. T. R. Kinasih, C. Machbub, L. Yulianti, and A. S. Rohman, "Two-stage multiple object detection using CNN and correlative filter for accuracy improvement", *Heliyon*, vol. 9, no. 1, pp. 1-18, 2023.

[30] M. Ming, R. Wang, H. Ishibuchi, and T. Zhang, "A Novel Dual-Stage Dual-Population Evolutionary Algorithm for Constrained Multiobjective Optimization", *IEEE Transactions on Evolutionary*

Computation, vol. 26, no.5, pp. 1129–1143, 2022.

[31] S. Sendari, A. N. Afandi, I. A. E. Zaeni, Y. D. Mahandi, K. Hirasawa, and H. I. Lin, "Exploration of genetic network programming with two-stage reinforcement learning for mobile robot", *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 17, no. 3, pp. 1447–1454, 2019.