

Dual-camera hue, saturation, value-based team robot detection for wheeled soccer

Tigor Hamonangan Nasution¹, Aldo Stepanus Kaban¹, Seniman²

¹Department of Electrical Engineering, Faculty of Engineering, Universitas Sumatera Utara, Medan, Indonesia

²Department of Information Technology, Faculty of Computer Science and Information Technology, Universitas Sumatera Utara, Medan, Indonesia

Article Info

Article history:

Received Mar 12, 2025

Revised Jul 30, 2026

Accepted Aug 20, 2026

Keywords:

Contour filtering

Dual-camera vision

Hue, saturation, value segmentation

Omnivision

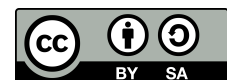
Team robot detection

Wheeled soccer robot

ABSTRACT

The Indonesian Wheeled Soccer Robot Contest requires reliable team robot detection to support robot maneuverability and coordination during matches. This study presents a lightweight dual-camera vision system that combines hue, saturation, value (HSV) color segmentation, morphological processing, and contour filtering to identify cyan and magenta team markers. A 5 MP front-facing camera was used for frontal observation, while a 0.9 MP camera combined with an omnivision mirror provided panoramic coverage. The system was examined through operational detection observations under stable indoor illumination of approximately 250–300 lux and unstable illumination of approximately 150–250 lux. Under stable illumination, the front-facing camera detected the target at observed distances up to 8.0 m. Under unstable illumination, the maximum observed range decreased to 3.0 m, indicating the sensitivity of fixed HSV thresholds to illumination variation. The panoramic camera provided complementary short-range directional information but was affected by its lower resolution and mirror distortion. Because repeated-trial logs, frame-level annotations, and processing-time measurements were not retained, the study does not report statistical detection accuracy or quantified real-time performance. Adaptive threshold estimation and systematic computational benchmarking are recommended for future development.

This is an open access article under the [CC BY-SA](#) license.



Corresponding Author:

Tigor Hamonangan Nasution

Department of Electrical Engineering, Faculty of Engineering, Universitas Sumatera Utara

Medan, Indonesia

Email: tigor.nasution@usu.ac.id

1. INTRODUCTION

Robotic soccer provides a challenging platform for evaluating perception, decision-making, coordination, and motion-control systems. In wheeled soccer robot competitions, visual detection of surrounding robots supports navigation, collision avoidance, positioning, and team coordination. Team robots can be distinguished using cyan or magenta visual markers attached to the robot body. Robotic soccer provides a challenging platform for evaluating perception, decision-making, coordination, localization, and motion-control systems. In wheeled soccer robot competitions, visual detection of surrounding robots supports navigation, collision avoidance, positioning, and team coordination [1]–[4].

Recent robot-soccer vision systems have increasingly employed learning-based object detectors to recognize robots, balls, goalposts, and field features under complex viewing conditions [5]–[11]. However, these

methods generally require annotated training datasets, model-training procedures, and dedicated computing resources. The deployment of learning-based vision on mobile and humanoid robots requires consideration of model size, inference latency, and hardware constraints [12]–[15]. Recent studies have also applied fully convolutional and encoder-decoder networks to field-line and soccer-field segmentation [16], [17]. Classical color-segmentation methods provide a simpler alternative because they do not require a training stage. Hue, saturation, value (HSV)-based segmentation is particularly useful because hue and saturation information can be processed separately from image brightness. Nevertheless, fixed HSV thresholds remain sensitive to illumination variation [18]–[20].

A methodological gap remains between highly adaptive learning-based detectors and relatively simple fixed-threshold methods. In particular, the operational effects of illumination variation and the complementary use of frontal and panoramic cameras for team-marker detection have received limited attention. Moreover, classical detection studies frequently report successful operation without clearly distinguishing observed detection range from statistical detection accuracy.

This study implements a dual-camera team robot detection system based on fixed HSV segmentation, morphological processing, and contour-based localization. The evaluation focuses on the maximum observed detection range under stable and unstable illumination and on the complementary coverage provided by frontal and panoramic cameras. Because the historical experiment did not retain repeated-trial logs, frame-level annotations, or timing measurements, the results are interpreted as operational observations rather than statistical accuracy estimates.

The contributions of this study are: i) the implementation of a dual-camera vision architecture combining frontal and panoramic observations; ii) the application of fixed HSV segmentation, morphological processing, and contour-based localization for detecting team markers; iii) an observational evaluation of detection range under two illumination conditions; and iv) an explicit analysis of the methodological and reproducibility limitations of the prototype.

The remainder of this paper is organized as follows. Section 2 describes the system architecture, image-processing stages, and experimental configuration. Section 3 presents the observed detection outcomes and their limitations. Section 4 provides the conclusion and directions for future work.

2. METHOD

This section describes the overall design of the detection system, the experimental setup, and the image processing pipeline. The available implementation details, hardware specifications, image-processing stages, and observational procedures are described to clarify the scope of the prototype and the limitations of the historical experiment.

2.1. System overview

The proposed system detects team robots by processing visual inputs captured from two cameras and transmitting detection results to a microcontroller for robot control. The overall architecture is illustrated in Figure 1.

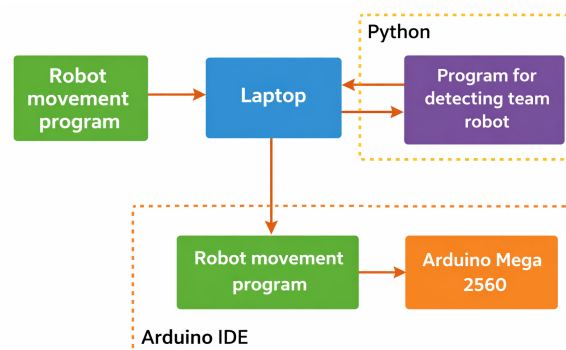


Figure 1. Architecture of the dual-camera team robot detection system

As shown in Figure 1, the laptop runs two programs: the detection algorithm written in Python using OpenCV, and the robot control program [21], [22]. The detection module processes the video feed from Camera 1 (5 MP) and Camera 2 (0.9 MP with omnivision mirror). The detected coordinates are then sent as character data to the Arduino Mega 2560 via serial communication [23]–[25]. The Arduino, programmed using the Arduino IDE [26] translates the received commands into motor actions through the BTS7960 motor driver [27].

The processing workflow is shown in Figure 2. The system begins by acquiring a frame from the selected camera. The frame is converted from OpenCV's default BGR channel order to HSV color space. Fixed thresholds are then applied to isolate cyan and magenta marker regions [28], [29]. Morphological opening and closing are applied before contour extraction. When a candidate marker is detected, its centroid is calculated, mapped to a predefined directional zone, and transmitted to the Arduino controller. Otherwise, the system proceeds to the next frame.

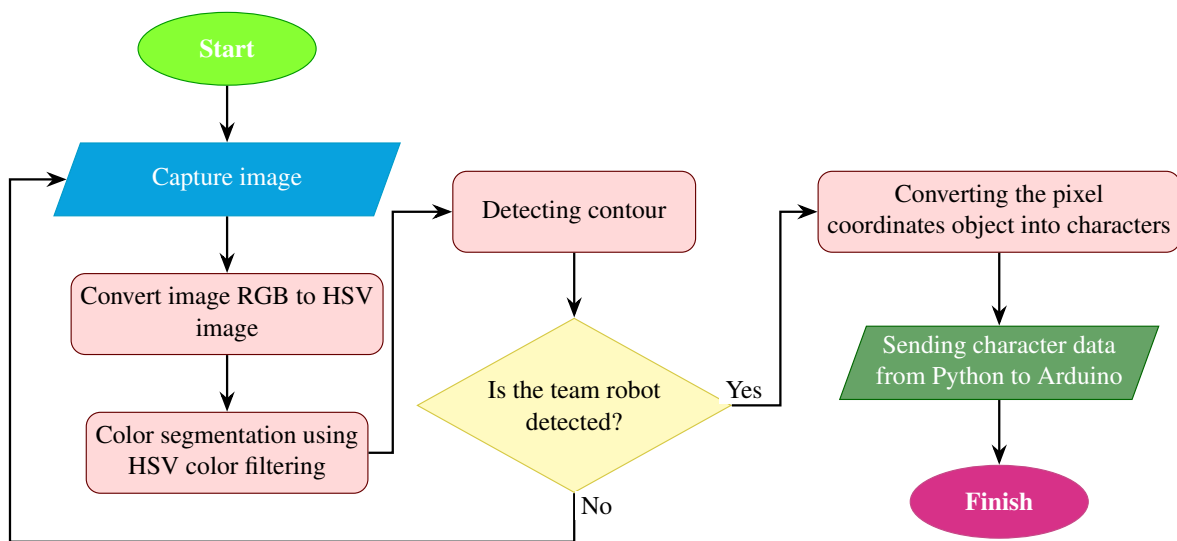


Figure 2. Processing flow of the team robot detection system

2.2. Experimental setup

Two illumination conditions were considered: stable indoor illumination of approximately 250–300 lux and unstable illumination of approximately 150–250 lux. The illumination level was observed using a Benetech GM1010 digital lux meter. Camera 1 was examined at distance intervals from 1.0 m to 8.5 m under stable illumination and from 1.0 m to 3.5 m under unstable illumination. At each reported distance, the recorded system output was documented as either detected or not detected. Because repeated-trial logs and frame-level annotations were not retained, these results are interpreted as operational detection-range observations rather than statistical accuracy estimates. The cyan and magenta markers had a trapezoidal shape with a 30 cm lower base, a 15 cm upper base, and a height of 20 cm.

2.3. Image acquisition

Video frames were captured in real time using two cameras: Camera 1 (NYK Nemesis A96, 5 MP, frontal view) and Camera 2 (Logitech C170, 0.9 MP). Camera 1 was used as a front-facing camera, whereas Camera 2 was equipped with a convex omnivision mirror for panoramic observation. The cameras provided a nominal input stream of approximately 23 fps. Omnidirectional and wide-field-of-view imagery can provide complementary semantic information for object-based localization, although image distortion and object scale remain important considerations [30], [31]. The acquired frames were resized to 640×480 pixels before image processing. The nominal camera frame rate represents the input stream and should not be interpreted as the effective algorithm throughput because processing latency was not instrumented. Camera 1 provided a direct forward view of the robot number background, while Camera 2 provided a 360° overhead reflection. Examples of captured images are shown in Figure 3.

Figure 3 illustrates the views produced by the two cameras. Camera 1 (Figure 3(a)) provides a direct frontal view of the team marker. Camera 2 (Figure 3(b)) captures a panoramic reflection through the omnivision

mirror. The lower resolution and optical distortion of Camera 2 reduce the apparent clarity of the target compared with the frontal camera. During prototype operation, Camera 2 provided complementary short-range directional observation, but systematic per-distance records for this camera were not retained.



Figure 3. Image captured by cameras; (a) Camera 1 and (b) Camera 2

2.4. Color space conversion

Camera frames acquired using OpenCV's default BGR channel order were converted to HSV using the `cv2.cvtColor()` function with the `cv2.COLOR_BGR2HSV` conversion flag [32]–[34]. In the 8-bit OpenCV representation, hue is stored in the range 0–180, whereas saturation and value are stored in the range 0–255. Separating chromatic information from the value component facilitates color-based segmentation, although it does not eliminate sensitivity to illumination variation [20], [35].

The cyan and magenta marker regions were segmented using fixed HSV thresholds selected through manual visual calibration on representative camera frames. The threshold bounds were adjusted until the target regions remained visible in the binary mask while most background regions were suppressed. Adaptive thresholding, automatic threshold optimization, and illumination-dependent recalibration were not implemented in the original system. The use of manually selected fixed thresholds is therefore recognized as a limitation under changing illumination.

Figure 4 presents the HSV conversion results obtained from the two camera configurations. As shown in Figure 4(a), Camera 1 produces a frontal HSV image in which the cyan and magenta marker regions are visually distinguishable, supporting marker segmentation at longer observation distances. In contrast, Figure 4(b) shows the HSV image obtained from Camera 2 through the omnivision mirror. This configuration provides a panoramic 360° field of view, although the lower 0.9 MP resolution and mirror-induced distortion reduce image sharpness compared with Camera 1. Overall, the representative images in Figures 4(a) and (b) illustrate that the target marker regions remain visually distinguishable in HSV space under the evaluated conditions.

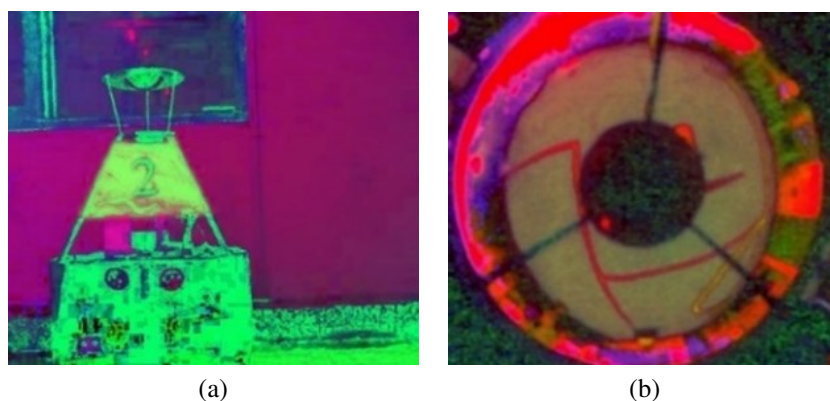


Figure 4. HSV image results; (a) Camera 1 and (b) Camera 2

After HSV conversion, the next step is binarization using predefined threshold ranges for cyan and magenta. This process separates the object (white pixels) from the background (black pixels), which is essential for contour detection in the next stage. Figure 5 shows the results of binarization for Camera 1. When the background is cyan (Figure 5(a)) or magenta (Figure 5(b)), the number region is clearly segmented in white while the surrounding area is black. In the representative frames, fixed HSV thresholding retained the principal marker regions under the illustrated controlled-lighting condition.



Figure 5. Binarization results of Camera 1 robot images; (a) cyan background and (b) magenta background

Figure 6 presents the binarization of Camera 2 with omnivision mirror input. Although the panoramic view introduces distortion and lower resolution, the target region can still be segmented as white against a black background. This enables detection of nearby team robots within a 360° coverage area, complementing the longer detection range of Camera 1.

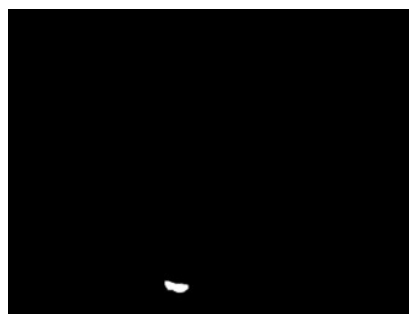


Figure 6. Binarization result of Camera 2 image

2.5. Morphological filtering

Morphological opening and closing were included before contour extraction using a 5×5 kernel. Opening was intended to suppress isolated foreground pixels, whereas closing was intended to fill small discontinuities within the segmented marker regions. A separate ablation experiment was not conducted in the original study. Therefore, the independent quantitative contribution of morphological filtering to false-positive reduction cannot be determined from the available experimental records.

2.6. Segmentation and contour detection

Contours were extracted from the binary mask to identify candidate marker regions. A dominant contour corresponding to the segmented marker was used to obtain a bounding rectangle and centroid. The centroid coordinates were subsequently mapped to predefined directional zones. Because the original source code was not archived, exact contour-area thresholds and rejection criteria cannot be independently verified.

2.7. Identification and data transmission

Detected robot positions were mapped to discrete image zones for easier decision-making. For Camera 1, the 640×480 frame was divided into 12 rectangular regions plus a central zone, enabling the system

to map centroid coordinates into symbolic labels. This division scheme is illustrated in Figure 7. In a similar manner, Camera 2 employed a quadrant-based division aligned with its 360° panoramic coverage. By partitioning the frame into four major quadrants (p–s), the system could associate detected objects with their approximate direction, as seen in Figure 8.

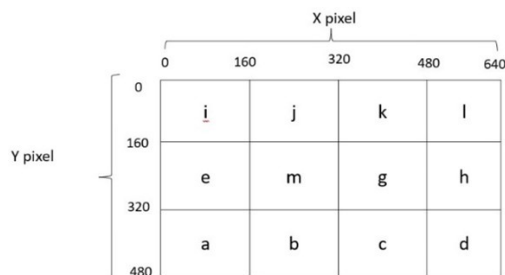


Figure 7. Illustration of image ratio division on camera

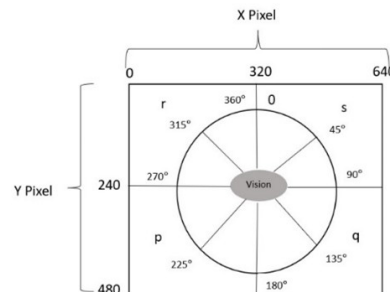


Figure 8. Illustration of image ratio division on Camera 2

Once the image was segmented, the system marked detected objects with bounding boxes and centroid points. For Camera 1, the bounding box (green) and centroid marker (red) were generated over the magenta background of the robot, and the centroid was then converted into a zone label. The detection output is depicted in Figure 9. A comparable process was carried out using Camera 2. Although the omnivision view introduced distortion and lower clarity, the centroid of the detected robot was still successfully localized in one of the four predefined quadrants, as shown in Figure 10. The quadrant label was then transmitted to the Arduino as character data for further action.



Figure 9. Camera 1 object detection coordinates result

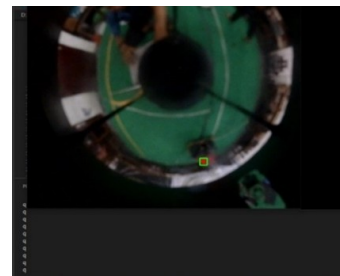


Figure 10. Camera 2 object detection coordinates result

2.8. Implementation details and reproducibility limitations

The available implementation records identify the principal hardware and software components used in the prototype. These details provide a partial description of the experimental configuration. However, the original source code, exact HSV threshold values, complete raw video recordings, frame-level annotations, and repeated-trial logs were not archived. Consequently, exact reproduction of the historical experiment cannot be guaranteed.

The documented implementation details are:

- Python 3.10.6, OpenCV 4.6.0, and NumPy 1.23;
- Arduino IDE 1.8.19 and Arduino Mega 2560 R3;
- Camera 1: NYK Nemesis A96, 5 MP;
- Camera 2: Logitech C170, 0.9 MP, with an omnivision mirror;
- Benetech GM1010 digital lux meter;
- Input image dimensions of 640×480 pixels;
- Nominal camera input rate of approximately 23 fps;
- Observed Camera 1 distance intervals of 1.0–8.5 m under stable illumination and 1.0–3.5 m under unstable illumination.

The information is therefore presented as an implementation description that can support the design of a future replication study rather than as a fully reproducible experimental package.

3. RESULTS AND DISCUSSION

This section presents the experimental results of the proposed HSV and contour filtering method for team robot detection. The results are critically discussed to highlight strengths, limitations, and comparisons with related work.

3.1. Preparation stage

Before testing, two preparation steps were performed. First, cyan and magenta number backgrounds were attached to the robots in trapezoidal shapes (30 cm base, 15 cm top, and 20 cm height) to conform to KRSBI-B competition standards. Second, the hardware setup included two types of cameras: Camera 1 and Camera 2. The placement of the number backgrounds and cameras on the wheeled soccer robots is illustrated in Figure 11.

As shown in Figure 11, the magenta and cyan number backgrounds serve as visual markers for team identification. Camera 1 is positioned at the front of the robot to capture direct views of these markers for long-range detection. Meanwhile, Camera 2 is mounted below the omnivision mirror to capture a panoramic 360° view, enabling short-range awareness of surrounding robots. This configuration ensures both frontal precision and panoramic coverage during detection.

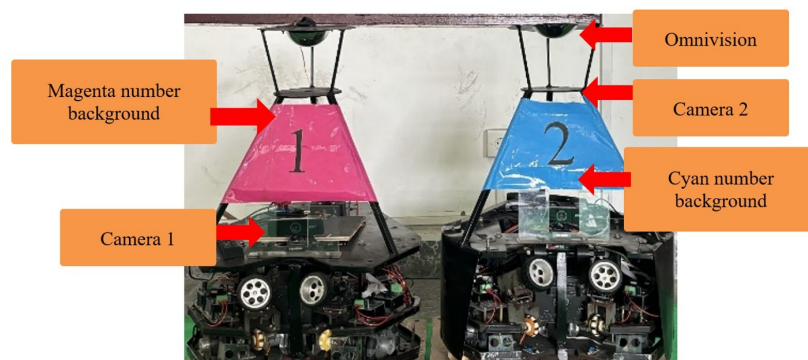


Figure 11. Wheeled soccer robot

3.2. Observed detection range under stable illumination

Camera 1 was observed at distance intervals from 1.0 m to 8.5 m under stable indoor illumination of approximately 250–300 lux. Table 1 presents the recorded detection outcome at each distance. Each row represents the recorded outcome at one observation distance. The table does not represent repeated trials or a statistical detection-accuracy measurement.

As shown in Table 1, the marker was detected at the reported observation points from 1.0 m to 8.0 m and was not detected at 8.5 m. Accordingly, 8.0 m is reported as the maximum observed detection range under the evaluated stable-lighting condition. This result should not be interpreted as a probabilistic detection limit or a statistical accuracy estimate. The unsuccessful outcome at 8.5 m may be associated with reduced apparent marker size, image resolution, camera focus, threshold selection, or other unmeasured imaging factors.

3.3. Observed detection range under unstable illumination

To assess the effect of varying illumination, Camera 1 was tested under unstable lighting conditions (150–250 lux). The recorded outcomes at six observation distances are presented in Table 2. Each row represents the recorded outcome at one observation distance and does not constitute a repeated-trial accuracy measurement.

Under unstable illumination, the marker was detected at the reported observation points from 1.0 m to 3.0 m and was not detected at 3.5 m. The maximum observed range therefore decreased from 8.0 m under

stable illumination to 3.0 m under unstable illumination. This corresponds to a 62.5% reduction in the maximum observed operational range:

$$\frac{8.0 - 3.0}{8.0} \times 100\% = 62.5\% \quad (1)$$

This percentage represents the reduction in observed detection range and must not be interpreted as classification accuracy. The result indicates that fixed HSV thresholds are sensitive to illumination variation because changes in brightness and saturation may shift target pixels outside the manually selected threshold ranges.

Table 1. Observed Camera 1 detection outcomes under stable illumination

No.	Observation distance (m)	Detection outcome
1	1.0	Detected
2	1.5	Detected
3	2.0	Detected
4	2.5	Detected
5	3.0	Detected
6	3.5	Detected
7	4.0	Detected
8	4.5	Detected
9	5.0	Detected
10	5.5	Detected
11	6.0	Detected
12	6.5	Detected
13	7.0	Detected
14	7.5	Detected
15	8.0	Detected
16	8.5	Not detected

Table 2. Observed Camera 1 detection outcomes under unstable illumination

No.	Observation distance (m)	Detection outcome
1	1.0	Detected
2	1.5	Detected
3	2.0	Detected
4	2.5	Detected
5	3.0	Detected
6	3.5	Not detected

3.4. Comparative discussion

The proposed pipeline does not require an annotated training dataset or a model-training stage because it relies on fixed color segmentation and contour processing. Nevertheless, a same-dataset quantitative comparison with RGB thresholding or a learning-based detector was not performed in the original experiment. The present study therefore does not claim superior or comparable detection performance relative to previous approaches.

Comparisons with published studies are used only to contextualize differences in algorithmic complexity, training requirements, target objects, and evaluation procedures. Results reported by other studies were obtained using different datasets, cameras, computing platforms, and performance metrics and therefore cannot be interpreted as a direct baseline for the present prototype.

The observations provide three main findings:

- Illumination sensitivity:** the maximum observed range decreased under unstable illumination, indicating the limitation of manually selected fixed HSV thresholds.
- Coverage trade-off:** the frontal camera provided longer observed range, whereas the omnivision camera provided complementary short-range directional coverage.
- Computational measurement limitation:** processing time, memory usage, processor load, and effective algorithm frame rate were not measured; therefore, computational superiority or quantified real-time performance cannot be claimed.

3.5. Study limitations

Several limitations should be considered when interpreting the findings. First, fixed HSV thresholds were selected manually, and adaptive or automatically optimized thresholding was not implemented. Second, the historical experiment did not retain repeated-trial logs, complete raw video recordings, or frame-level annotations. Therefore, precision, recall, F1-score, false-positive rate, confidence intervals, and statistical detection accuracy could not be calculated. Third, no same-dataset RGB baseline or morphological ablation experiment was performed. Fourth, processing time per frame, effective frame rate, memory usage, and processor load were not instrumented. The nominal camera input rate therefore cannot be interpreted as algorithm throughput. Fifth, systematic per-distance records for the panoramic camera were not retained. Finally, the lower resolution and mirror distortion of Camera 2 reduced the clarity of its panoramic observations. These limitations restrict the conclusions to the reported operational observations.

4. CONCLUSION

This study implemented a dual-camera team robot detection system using fixed HSV segmentation, morphological processing, and contour-based localization. Under stable indoor illumination of approximately 250–300 lux, the front-facing camera detected the team marker at reported observation distances up to 8.0 m. Under unstable illumination of approximately 150–250 lux, the maximum observed range decreased to 3.0 m, corresponding to a 62.5% reduction in operational detection range. The panoramic camera provided complementary short-range directional observation but was affected by its lower resolution and mirror distortion. The findings indicate that fixed HSV segmentation can support marker detection under controlled illumination but remains sensitive to environmental variation. Because repeated-trial logs, frame-level annotations, direct baseline results, and processing-time measurements were not retained, the study does not claim statistical detection accuracy, quantified false-positive reduction, or measured real-time performance. Future studies should collect an annotated dataset with repeated trials and evaluate adaptive thresholding, morphological ablation, an RGB baseline, precision, recall, F1-score, and processing latency.

FUNDING INFORMATION

The authors acknowledge that this research was financially supported by Universitas Sumatera Utara.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Tigor Hamonangan Nasution	✓	✓		✓	✓	✓			✓	✓		✓	✓	✓
Aldo Stepanus Kaban	✓	✓	✓	✓	✓	✓		✓	✓				✓	
Seniman	✓			✓						✓		✓		

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal Analysis

I : **I**nterpretation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**dit

Vi : **V**isualization

Su : **S**upervision

P : **P**roject Administration

Fu : **F**unding Acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors also declare that they have no non-financial competing interests, including political, personal, religious, ideological, academic, or intellectual interests, that could be perceived as influencing this work.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [initials: TN]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

REFERENCES

- [1] C. Hong, I. Jeong, L. F. Vecchietti, D. Har, and J. -H. Kim, "AI World Cup: Robot-Soccer-Based Competitions," *IEEE Transactions on Games*, vol. 13, no. 4, pp. 330–341, 2021, doi: 10.1109/TG.2021.3065410.
- [2] E. Antonioni, V. Suriani, F. Riccio, and D. Nardi, "Game Strategies for Physical Robot Soccer Players: A Survey," *IEEE Transactions on Games*, vol. 13, no. 4, pp. 342–357, 2021, doi: 10.1109/TG.2021.3075065.
- [3] M. Abreu, T. Silva, H. Teixeira, L. P. Reis, and N. Lau, "6D Localization and Kicking for Humanoid Robotic Soccer," *Journal of Intelligent & Robotic Systems*, vol. 102, 2021, doi: 10.1007/s10846-021-01385-3.
- [4] J. G. Melo, L. Cavalcanti, R. Joaquim, V. Araújo, and E. Barros, "Onboard Perception and Localization for Resource-Constrained Dynamic Environments: A RoboCup Small Size League Case Study," *Journal of Intelligent & Robotic Systems*, vol. 111, 2025, doi: 10.1007/s10846-025-02259-8.
- [5] N. Cruz, F. Leiva, and J. Ruiz-del-Solar, "Deep Learning Applied to Humanoid Soccer Robotics: Playing without Using Any Color Information," *Autonomous Robots*, vol. 45, pp. 335–350, 2021, doi: 10.1007/s10514-021-09966-9.
- [6] D. D. R. Meneghetti, T. P. D. Homem, J. H. R. de Oliveira, I. J. da Silva, D. H. Perico, and R. A. d. C. Bianchi, "Detecting Soccer Balls with Reduced Neural Networks: A Comparison of Multiple Architectures under Constrained Hardware Scenarios," *Journal of Intelligent & Robotic Systems*, vol. 101, 53, 2021, doi: 10.1007/s10846-021-01336-y.
- [7] M. and V. Estivill-Castro, "Fully Neural Object Detection Solutions for Robot Soccer," *Neural Computing and Applications*, vol. 34, pp. 21419–21432, 2022, doi: 10.1007/s00521-021-05972-1.
- [8] J. Xue *et al.*, "Lightweight Visual Backbone Network with Enhanced Comprehensive Strength Through Context-Aware Dual Attention Mechanism," *Neurocomputing*, vol. 624, 2025, doi: 10.1016/j.neucom.2025.129449.
- [9] Setiawardhana, I. K. Wibowo, and N. A. H. Bernardt, "Prediction of Ball Position Using CNN Methods With Zed Camera on Goalkeeper Robot Application," *IEEE Access*, vol. 13, pp. 41559–41570, 2025, doi: 10.1109/ACCESS.2025.3546346.
- [10] H. Jati, N. A. Ilyasa, and D. D. Dominic, "Enhancing Humanoid Robot Soccer Ball Tracking, Goal Alignment, and Robot Avoidance Using YOLO-NAS," *Journal of Robotics and Control*, vol. 5, no. 3, pp. 829–838, 2024, doi: 10.18196/jrc.v5i3.21839.
- [11] M. S. Ahamed, J. Pey, S. M. B. P. Samarakoon, M. A. V. J. Muthugala, and M. R. Elara, "Reinforcement Learning for Reconfigurable Robotic Soccer," *IEEE Access*, vol. 13, pp. 22314–22324, 2025, doi: 10.1109/ACCESS.2025.3536497.
- [12] S. N. Aslan, A. Uçar, and C. Güzelis, "New Convolutional Neural Network Models for Efficient Object Recognition with Humanoid Robots," *Journal of Information and Telecommunication*, vol. 6, no. 1, pp. 63–82, 2022, doi: 10.1080/24751839.2021.1983331.
- [13] J. A. Vicente-Martínez, M. Márquez-Olivera, A. García-Aliaga, and V. Hernández-Herrera, "Adaptation of YOLOv7 and YOLOv7-Tiny for Soccer-Ball Multi-Detection with DeepSORT for Tracking by a Semi-Supervised System," *Sensors*, vol. 23, no. 21, 8693, 2023, doi: 10.3390/s23218693.
- [14] Y. Ye, X. Ma, X. Zhou, G. Bao, W. Wan, and S. Cai, "Dynamic and Real-Time Object Detection Based on Deep Learning for Home Service Robots," *Sensors*, vol. 23, no. 23, 2023, doi: 10.3390/s23239482.
- [15] T. H. Nasution, A. Simon, F. Fahmi, K. Tanjung, M. Zarlis, and N. Noer, "Analysis of the use of CMUcam5 Pixy camera in wheeled soccer robots," in *The 2020 International Conference on Information Technology and Engineering Management (ITEM 2020)*, Batam, Indonesia, vol. 851, 2020, doi: 10.1088/1757-899X/851/1/012034.
- [16] D. Zhou, G. Chen, and F. Xu, "Application of Deep Learning Technology in Strength Training of Football Players and Field Line Detection of Football Robots," *Frontiers in Neurorobotics*, vol. 16, p. 867028, 2022, doi: 10.3389/fnbot.2022.867028.
- [17] O. H. R. Guimarães, M. R. O. A. Maximo, and J. M. P. de Oliveira, "Comparison and Optimization of U-Net and SegNet Encoder-Decoder Architectures for Soccer Field Segmentation in RoboCup," *Journal of Intelligent & Robotic Systems*, vol. 112, 2026, doi: 10.1007/s10846-025-02280-x.
- [18] L. He, X. Cheng, A. Jiwa, D. Li, J. Fang, and Z. Du, "Zanthoxylum bungeanum Fruit Detection by Adaptive Thresholds in HSV Space for an Automatic Picking System," *IEEE Sensors Journal*, vol. 23, pp. 14471–14486, 2023, doi: 10.1109/JSEN.2023.3277042.
- [19] Y. Ito, C. Premachandra, S. Sumathipala, H. W. H. Premachandra, and B. S. Sudantha, "Tactile Paving Detection by Dynamic Thresholding Based on HSV Space Analysis for Developing a Walking Support System," *IEEE Access*, vol. 9, pp. 20358–20367, 2021, doi: 10.1109/ACCESS.2021.3055342.
- [20] H. Zhong and R. Wang, "A visual-degradation-inspired model with HSV color-encoding for contour detection," *Journal of Neuroscience Methods*, vol. 369, 2022, doi: 10.1016/J.JNEUMETH.2021.109423.
- [21] P. Kohut and K. Skop, "Vision Systems for a UR5 Cobot on a Quality Control Robotic Station," *Applied Sciences*, vol. 14, no. 20, p. 9469, 2024, doi: 10.3390/app14209469.
- [22] A. A. Santos *et al.*, "Integration of Artificial Vision and Image Processing into a Pick and Place Collaborative Robotic System," *Journal of Intelligent & Robotic Systems*, vol. 110, 2024, doi: 10.1007/s10846-024-02195-z.
- [23] A. T. Oyelami, J. A. Oyadokun, O. A. Akintunlaji, and G. C. Ihenacho, "Low-cost multi-sensing fire-fighting robot with obstacle avoidance mechanism," *IAES International Journal of Robotics and Automation (IJRA)*, vol. 13, no. 4, pp. 373–379, 2024, doi: 10.11591/IJRA.V13I4.PP373-379.
- [24] M. F. Aqillah, R. Mardiaty, and A. E. Setiawan, "Prototype of Robot Movement Navigation System Using Pixy Camera (CMUCAM 5)," in *2022 8th International Conference on Wireless and Telematics (ICWT)*, 2022, pp. 1–6, doi: 10.1109/ICWT55831.2022.9935409.
- [25] H. Khairam, Y. M. Choong, N. S. N. Ismadi, W. A. F. W. Othman, A. A. A. Wahab, and S. S. N. Alhady, "Design and development of a low-cost pole climbing robot using Arduino Mega," in *International Virtual Conference on Intelligent Robotics, Mechatronics and Automation Systems 2021 (IRMAS 2021)*, vol. 1969, 2021, doi: 10.1088/1742-6596/1969/1/012008.
- [26] B. Perumal, A. S. Balaji, M. V. Dharshini, C. Aravind, J. Deny, and R. Rajasudharsan, "Detection of Food Adulteration using Arduino IDE," in *Proceedings of the 2nd International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2021,

- pp. 262–267, doi: 10.1109/ICESC51422.2021.9532720.
- [27] V. Bugade, P. Chougale, P. Katkar, S. Lavhate, and A. Bhosale, “BTS7960 Motor Drive: Precision Speed Modulation for PMDC Motors,” in *2024 3rd International Conference for Advancement in Technology (ICONAT)*, 2024, pp. 1–5, doi: 10.1109/ICONAT61936.2024.10774735.
- [28] N. W. Christian and F. T. Sabilillah, “Color Detection Using Webcam with Matlab HSV Color Model Segmentation Based,” *International Journal of Engineering Computing Advanced Research*, vol. 1, no. 1, 43–51, 2024.
- [29] A. Vas and G. A. Dsouza, “Object Tracing with Colour range filtering in HSV Colour space and Object Following with Ros2,” in *2023 Global Conference on Information Technologies and Communications (GCITC)*, 2023, doi: 10.1109/GCITC60406.2023.10426509.
- [30] X. Tian, “Analysis of Soccer Robot Localization Based on UKF Sampling and Sobel Operator,” *IEEE Access*, vol. 12, pp. 106951–106962, 2024, doi: 10.1109/ACCESS.2024.3434514.
- [31] I. Uygur, R. Miyagusuku, S. Pathak, H. Asama, and A. Yamashita, “Data Fusion for Sparse Semantic Localization Based on Object Detection,” *Journal of Robotics and Mechatronics*, vol. 36, no. 2, pp. 375–387, 2024, doi: 10.20965/jrm.2024.p0375.
- [32] R. TH. Hasan and A. B. Sallow, “Face Detection and Recognition Using OpenCV,” *Journal of Soft Computing and Data Mining*, vol. 2, no. 2, pp. 86–97, 2021, doi: 10.30880/jscdm.2021.02.02.008.
- [33] T. S. Rathnayake, D. K. Prasanga, and A. M. H. S. Abeykoon, “3D Localization of an Object Using a Monocular Camera,” *IECON 2023–49th Annual Conference of the IEEE Industrial Electronics Society*, 2023, pp. 1–6, doi: 10.1109/IECON51785.2023.10312377.
- [34] J. Sigut, M. Castro, R. Arnay, and M. Sigut, “OpenCV Basics: A Mobile Application to Support the Teaching of Computer Vision Concepts,” *IEEE Transactions on Education*, vol. 63, no. 4, pp. 328–335, 2020, doi: 10.1109/TE.2020.2993013.
- [35] S. R. Prakash and P. N. Singh, “Background region based Face orientation prediction through HSV skin color model and K-Means clustering,” *International Journal of Information Technology*, vol. 15, pp. 1275–1288, 2023, doi: 10.1007/s41870-023-01174-1.

BIOGRAPHIES OF AUTHORS



Tigor Hamonangan Nasution     is a lecturer in the Department of Electrical Engineering at Universitas Sumatera Utara, Indonesia, where he has been serving since 2014. He obtained his master's degree in Electrical Engineering in 2014 and completed his Doctorate in Computer Science at Universitas Sumatera Utara in 2025. He currently serves as the Director of the Directorate of Learning Digitalization at Universitas Sumatera Utara, focusing on the development and implementation of technology-enhanced learning systems. He is a Senior Member of IEEE and actively conducts research in computer engineering, particularly in embedded systems, robotics, and artificial intelligence. In addition to his academic and research activities, he also contributes to student development by serving as an advisor to the Robotics Student Activity Unit at Universitas Sumatera Utara. He can be contacted at email: tigor.nasution@usu.ac.id.



Aldo Stepanus Kaban     is an undergraduate student in the Department of Electrical Engineering at Universitas Sumatera Utara, Indonesia. During his studies, he has been actively involved in academic and research activities, including serving as a laboratory assistant in the Computer and Control Laboratory at the Department of Electrical Engineering, Faculty of Engineering, Universitas Sumatera Utara. He also previously served as the Chair of the Universitas Sumatera Utara Robotics Student Activity Unit, where he contributed to the development of student robotics projects and competitions. His interests include computer engineering and robotics, and he has participated in several research activities assisting lecturers in related fields. He can be contacted at email: aldokaban3009@students.usu.ac.id and aldokaban30@gmail.com.



Seniman     is a lecturer in the Department of Information Technology at Universitas Sumatera Utara, Indonesia. He has been actively involved in research in the field of computer science and has contributed to various scientific publications in related areas. In addition to his research activities, he also participates in mentoring student innovation programs, particularly in robotics competitions and technology-based projects. He can be contacted at email: pakniman@usu.ac.id.