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Implementation and Analysis of a Computer Vision-Based Ball Detection System for Robot Soccer in ROS Simulation

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ABSTRACT

This research investigates a computer vision-based ball detection system designed for robotic soccer applications, with a focus on assessing its efficiency across varying distances from 1 to 12 meters. The study utilizes the YOLOO (You Only Look Once) algorithm to evaluate the robot's detection accuracy, response times, and navigational performance in real time. A dataset composed of 3,400 images was created to facilitate the training and validation of the detection system under diverse lighting conditions. Findings revealed that the system achieved optimal detection accuracy of 70% at 1 meter, which decreased to 31% as the distance increased to 12 meters. The average response time for detection was recorded at 120 milliseconds for close distances, escalating to 228 milliseconds for farther distances. These results indicate the necessity for further enhancements in computer vision capabilities to improve interaction in dynamic settings such as robotic soccer. The study underscores both the potential and limitations of current detection methodologies, offering pathways for future advancements in robotic automation within competitive environments.

Keywords: Computer Vision; Deep Learning; Soccer Robot; Ball Detection; YOLO Algorithm.

Article History

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I. INTRODUCTION

The evolution of robotic technologies has dramatically advanced the capabilities of object detection, particularly in dynamically interactive environments such as soccer. Accurate object detection is vital for robots to make quick and precise decisions during gameplay. This chapter reviews existing literature on object detection methodologies relevant to robotics, highlighting current advancements, identifying gaps, and suggesting areas for further research. Traditional detection methods, such as edge detection, form the foundation upon which more advanced techniques are built. Various edge detection techniques that enhance image processing systems, emphasizing their role in robust object recognition [1]. Recent trends have shifted towards deep learning methodologies. For instance, the use of CNNs has proven effective across various applications. The effectiveness of the ResNet-50 model in detecting objects in complex scenarios, paving the way for similar applications in soccer robotics [2].

The You Only Look Once (YOLO) algorithm has been revolutionary for real-time object detection. Researchers [3] proposed enhancements to the YOLOv3 algorithm specifically for soccer robots, indicating the algorithm's adaptability to high-speed environments. This modification retains YOLO's characteristic speed while improving detection accuracy, which is vital for real-time decision-making. In addition, the importance of real-time ball detection approaches using YOLO technologies for soccer robots [4]. Their work established a connection between object detection and responsive robot actions during gameplay, offering insights into practical applications that enhance performance on the field. Moreover, research [14] provides a thorough examination of YOLOv3's performance across various robotic applications, supporting its implementation in dynamic environments like soccer fields. Their findings bolster the argument for adopting YOLO frameworks in effective robotic designs.

Despite advancements, there are significant challenges related to object tracking. Critically analyze different computer vision algorithms applied within soccer contexts, identifying limitations in existing methods that struggle to maintain tracking accuracy amid rapid movement [5]. This gap presents an opportunity for developing adaptive machine learning techniques to enhance tracking performance. Investigate techniques for the detection and classification of soccer balls, focusing on image processing

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strategies that enhance recognition accuracy [11]. Their findings highlight the importance of continually refining detection methods to serve the demands of robotic soccer applications.

The necessity for robust tracking methodologies suggests that deep learning frameworks are essential to address the challenges posed in real-time tracking and detection [6]. Their insights indicate the ongoing need for innovative solutions that can streamline the object detection process. As the landscape of object detection evolves, comprehensive surveys provide crucial insights into ongoing advancements. A thorough study on object detection methods, offering a detailed analysis of the strengths and weaknesses of contemporary techniques [9]. Their work informs future research directions by pinpointing significant gaps in current methodologies, particularly concerning the integration of detection systems into robotic applications. In addition, image processing techniques are tailored specifically for sports applications [10]. Their discussion highlights how techniques designed for sports can improve object detection in robotics, providing an essential link between traditional imaging methods and emerging robotic technologies used in dynamic environments like soccer. Similarly, an in-depth survey of various object detection techniques provides a contextual understanding of their strengths and weaknesses. Their analysis helps frame future directions for research by identifying gaps that still need to be addressed [13]. Furthermore, research [7] focused on real-time object detection through SSD (Single Shot MultiBox Detector) and MobileNet, mechanisms particularly relevant to robotic applications. Their research indicates substantial potential for enhancing soccer robot performance through the integration of advanced detection algorithms. Developing effective simulation environments is crucial for training soccer robots. A soccer robot simulator that incorporates advanced image processing techniques [8]. This work emphasizes how simulations can prepare robots for real-world gameplay by allowing for targeted training exercises that refine detection capabilities. In line with the application of OpenCV for real-time soccer ball detection, demonstrating how established image processing frameworks can be effectively utilized in real-time robotic applications [12]. Their findings suggest that traditional methods, when combined with modern algorithms, can cater to the demands of robotic soccer.

The continued evolution in object detection requires both innovation and adaptation. Researchers [15] conducted a comparative study of tracking algorithms, revealing varying effectiveness in sporting contexts, thus underscoring the need for techniques explicitly tailored to high-speed environments. The researchers [16] propose adaptations to YOLO frameworks aimed at improving the efficiency of object detection in robotic soccer. The research [17] discusses various deep learning methodologies explicitly designed for soccer ball detection, further validating the shift towards machine learning in enhancing detection capabilities. Their research underscores the necessity for continuous exploration of deep learning approaches to ensure effective performance in robotic systems. Furthermore, automated soccer ball detection using machine learning techniques presents evidence of the advantages of employing automated systems in sports applications [18]. Their work demonstrates the potential for significant advancements in how robots perceive and react to fast-moving objects on the field. Finally, researchers [19] conducted a thorough survey on the state-of-the-art in object detection methods. Their research stresses the importance of adapting to new advancements to address existing challenges effectively. By systematically reviewing various techniques, they provide essential insights that can guide ongoing research in robotics. Additionally, research [20] focused on dynamic ball detection using CNNs designed explicitly for soccer robots. Their innovative approaches underscore the continuing shift towards deep learning methodologies in enhancing the effectiveness of robotic systems in sports.

This study aims to explore the capabilities of a computer vision-based ball detection system within a robotic soccer environment. Specifically, it focuses on evaluating detection accuracy, response time, and performance across distances ranging from 1 to 12 meters, while considering the implications of various environmental factors on system performance.

II. METHOD

This chapter outlines the methodology employed to assess the performance of a computer vision-based ball detection system developed for robotic soccer applications. The approach encompasses the experimental setup, the design and implementation of the detection system, the data collection process, and the analytical methods used to evaluate the obtained results.

2.1. Experimental Setup

The experiments were carried out within a simulated environment utilizing ROS (Robot Operating System) and Gazebo. This setup was tailored specifically for testing the Computer Vision-Based Ball Detection System designed for robot soccer. The following elements were integral to the simulation.

1) Simulation Environment:
   A virtual soccer field measuring 12 meters by 8 meters was meticulously constructed within the Gazebo, adhering to the standards set by the *KRSBI Beroda* competition. This environment incorporated digital representations of critical components such as the ball and goalposts, facilitating a thorough assessment of the system's capabilities.
2) Robot Configuration
   The robot was designed as a 3D model and seamlessly integrated into the Gazebo simulation. This design included a wheeled locomotion system, allowing it to navigate effectively across the simulated field. A high-resolution camera mounted on the robot's front provides a comprehensive view necessary for detecting the soccer ball.
3) Camera Setup
   The camera was conFig.d to capture video at 30 frames per second, ensuring a steady stream of images that is crucial for real-time analysis and ball identification.

4) Processing Unit Simulation
The robot's onboard processing capabilities were represented in the simulation, mirroring the specifications of an MSI KATANA A15 B8V laptop. This included features such as an AMD Ryzen 7 5800H processor, an NVIDIA GeForce RTX 3060 graphics card, and 16 GB of RAM, along with 1 TB of SSD storage. This configuration equips the system with the requisite computational power for executing advanced computer vision algorithms effectively.
5) Field Marking
The simulated soccer field was accurately marked to reflect the layout required for the *KRSBI Beroda* competition, including specific zones for the ball and the robot's starting positions.
6) Trial Objectives
Each trial aimed to measure the performance of the ball detection system at various distances, specifically ranging from 1 to 12 meters. This variability was essential for assessing the reliability and effectiveness of the detection system in different scenarios.

2.2. Detection System Design

The primary objective of this project was to develop a robust computer vision system capable of detecting a soccer ball in a simulated environment using ROS and Gazebo. The detection process was structured into a series of systematic steps, as outlined below:

1) Flow Overview
From building the simulation environment to integrating real-time object identification and autonomous robot control, the system created in this study adheres to a disciplined methodology based on Fig.1. The first step involves creating a simulation environment with Gazebo, where a CAD-designed omni-wheeled robot model that is transferred to ROS in the URDF format is set up on a level surface that resembles a miniature soccer field. To capture live image frames, a virtual camera is put atop the robot. The object detection module uses these pictures as visual input. The rostopic /final/camera1/image_raw, which publishes data in the sensor_msgs/Image format, integrates the camera into the ROS environment.

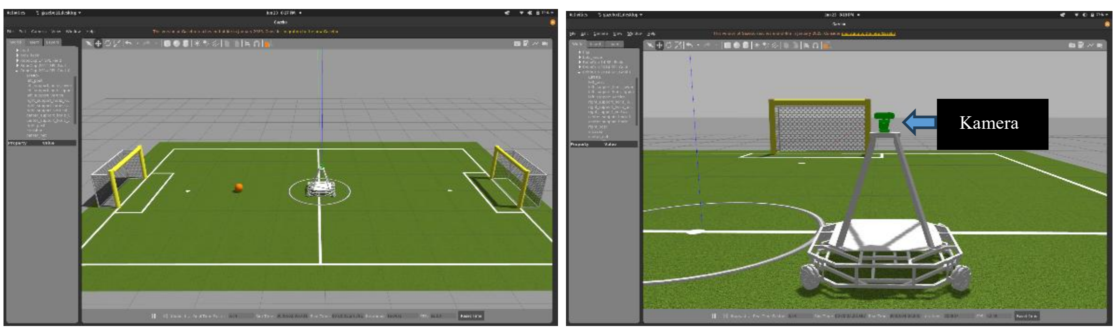

Fig.1. Robot, Camera, Ball and Arena View Inside the Gazebo

Using the final_world1.The next stage in the system execution process is launching the file to start the simulation. The initializing for the Gazebo environment, spawning the robot, positioning the ball object, and turning on the camera topic are all handled by this launch file. The yolov8.py node is used to activate the object detection system after the simulation environment has been launched. This Python script subscribes to the camera topic in real time and imports the trained YOLOv8 model. To determine the location of the soccer ball, it uses the Ultralytics library in inference mode to process the incoming image stream. The robot's control system then receives the ball coordinates that were found in the picture frame. The ball's horizontal offset within the frame is used to create the proper linear and angular velocity commands in a proportional control strategy. This makes it possible for the robot to change its orientation and approach the ball on its own. This pipeline illustrates a thorough visual perception and control system, from environment setup and data collecting to model training and integration. It satisfies the main objectives of this study by enabling the robot to recognize and move toward the ball in real time within the simulated environment.

2) Dataset Creation
A comprehensive dataset was compiled, comprising 3,400 images of the soccer ball taken from various angles and under differing lighting conditions. This dataset included both positive samples (images containing the ball) and negative samples (images without the ball), ensuring a balanced representation that enhances the model's performance in varied scenarios. One of the dataset images used to train the YOLOv8 object detection model is seen in Fig.2. An orange ball is placed in front of a goalpost on a green field in this image, which was shot from the Gazebo simulation environment. This picture is from a synthetic dataset that was created with a virtual camera installed on a robot simulator. The purpose of the dataset was to train the model to identify and detect the ball in a range of lighting situations, locations, and angles. The visual elements, such as the stark contrast between the orange ball, green field, and yellow goalpost, improve the model's capacity to learn and generalize the object of interest.

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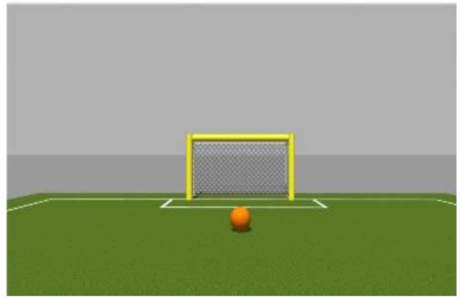

Fig.2. Dataset Images

3) Model Selection

YOLOv8s (You Only Look Once version 8 Small variant), the most recent development in the YOLO family created by Ultralytics, is the object detection model utilized in this study. Model size, detection accuracy, and real-time processing capacity were all balanced in YOLOv8s, which makes it ideal for robotic applications where computing economy is crucial. YOLOv8 uses an anchor-free architecture that predicts the centre of objects and bounding boxes directly, in contrast to previous iterations that depended on anchor-based detection. This simplifies training and speeds up inference. The three primary parts of YOLOv8s' architecture are the head, neck, and backbone. The backbone, which is based on a modified CSPDarknet and is in charge of extracting features from input photos, enables effective learning at a lower computational cost. The neck improves the model's capacity to identify objects of different sizes by combining data from several scales using a Path Aggregation Network (PANet). Object classes and bounding box coordinates are among the final predictions generated by the head, which is detached for classification and regression tasks. Because of its lightweight design and excellent accuracy in detecting small objects like a soccer ball, YOLOv8s is very useful in this research. The robot was able to detect and track the ball in real time since the model was trained on artificial picture data created from a Gazebo-simulated environment. Because of this, YOLOv8s is a good option for the visual perception system in applications involving autonomous robotic soccer.

4) Training the Model

Three subsets of the dataset 70% for training, 20% for validation, and 10% for testing, were used in this investigation, with results as shown in Fig.3. This divide allowed for fair judgment on unseen data. It guaranteed that the model could be trained efficiently.

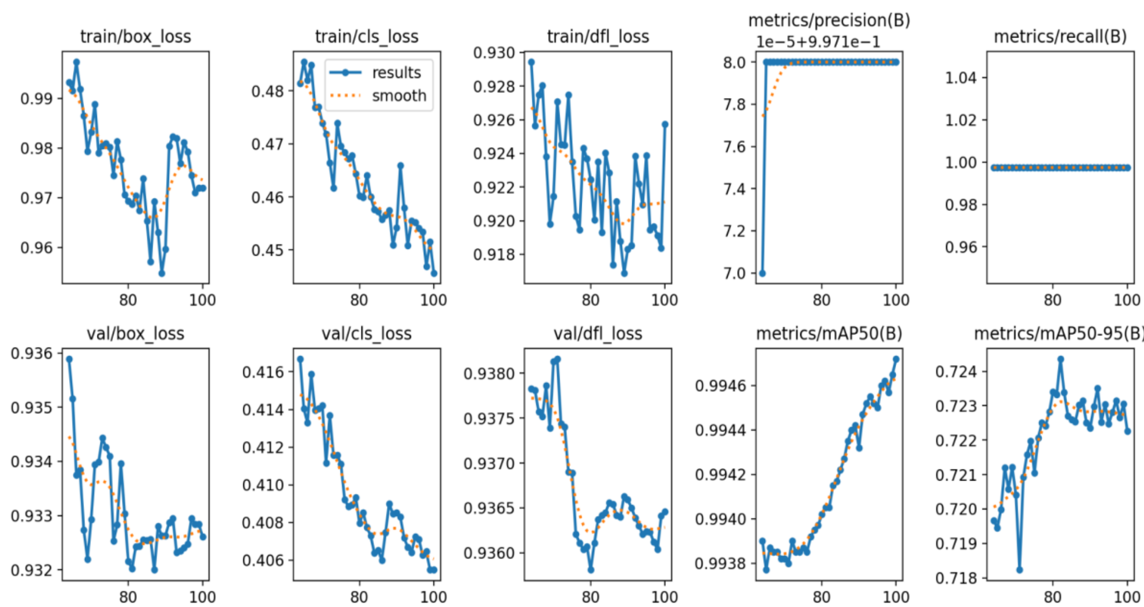

Fig.3 Training Results Graph

Initially, pre-trained weights from a large-scale object identification dataset, like COCO, were used to train the YOLOv8s model. This method enhanced baseline performance and allowed for quicker convergence. After that, the model was particularly adjusted to recognize soccer balls in the simulated environment. Based on repeated experimentation, several hyperparameters were changed to optimize the training process. The batch size was set to 16, the learning rate was set at 0.001, and there were 100 training epochs. To balance detection accuracy and training efficiency, these parameters were used. Additionally, data augmentation methods such as image rotation, scaling, and colour modification were used to improve the dataset. The model's resilience to changes in illumination, camera angles, and ball placements that are frequently seen in the simulation environment was enhanced by these additions. To benefit from high-performance computation, the training was

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carried out on Google Colab with GPU acceleration. Important performance indicators like box loss, categorization loss, recall, precision, and mean Average Precision (mAP) were tracked constantly during the training process. With a mAP50 of nearly 0.995 and a recall of 1.0, the training results showed excellent model performance, suggesting that the YOLOv8s model was very accurate and dependable in identifying the soccer ball under a variety of simulated scenarios.

5) Validation and Testing
The trained model was validated using a separate dataset. Performance metrics, including precision, recall, and F1 score, were calculated to assess the model's accuracy and reliability. Following validation, the model was tested in real-time scenarios in the Gazebo simulation. This involved operating the robot within the virtual environment, allowing it to use the trained model to detect the ball during actual movement trials.

2.3. *Flow Diagram of the Computer Vision-Based Ball Detection System*

Fig.4 illustrates the step-by-step process of the Computer Vision-Based Ball Detection System. This diagram serves as a visual guide to understanding the workflow of the system. To fully comprehend how the system operates from image capture through data processing to executing movement commands based on ball detection, refer to Fig.1. It highlights key phases, including decision-making points and the actions taken at each stage. By examining this flowchart, readers can better grasp the intricate processes involved in the system's functionality.

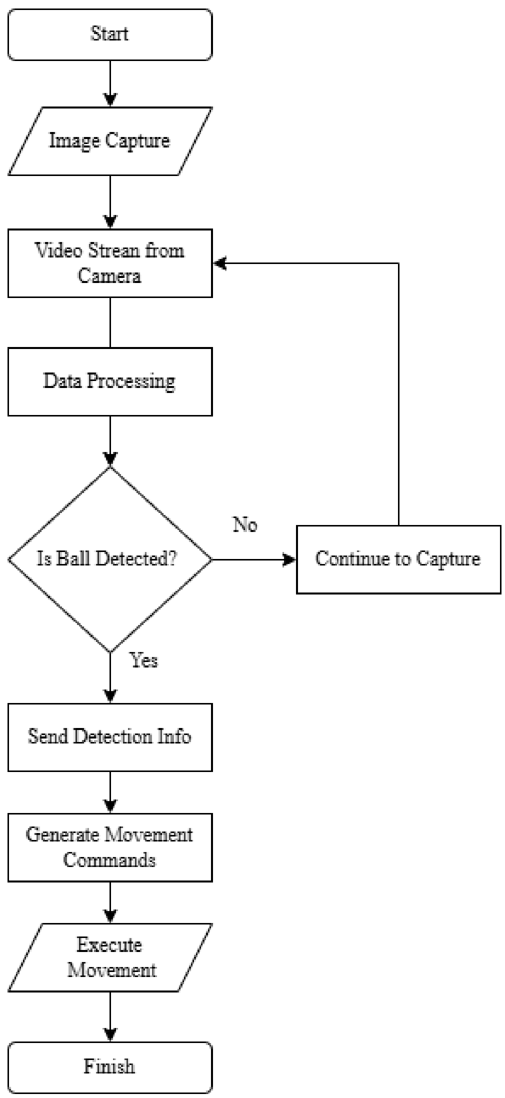

Fig. 4 Flow Diagram of the Computer Vision-Based Ball Detection System

The process begins with the Start point, where the system initializes and sets parameters for image capture and processing. Following this, the Image Capture step involves a camera continuously capturing video frames at a specified frame rate, such as 30 frames per second. These captured frames are then streamed in real-time, allowing for immediate processing in the Data Processing phase. Here, the system employs the YOLO (You Only Look Once) algorithm to identify the presence of a soccer ball. YOLO utilizes a convolutional neural network (CNN), which divides each frame into a grid to make predictions about object locations.

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These captured frames are then streamed in real-time, allowing for immediate processing in the Data Processing phase. Here, the system employs the YOLO (You Only Look Once) algorithm to identify the presence of a soccer ball. YOLO utilizes a convolutional neural network (CNN), which divides each frame into a grid to make predictions about object locations. The next step, Ball Detected, acts as a decision-making point where the algorithm determines whether the ball is present based on the processed frame. If the ball is detected, the system proceeds to the Send Detection Info step, where the coordinates of the ball are relayed to the movement control system. Based on these coordinates, the system moves to Generate Movement Commands, calculating the linear and angular velocities required to approach the ball. For instance, the linear velocity can be expressed as $Linear\ Velocity = kp \cdot Distance\ to\ Ball$, where kp is a proportionality constant, and the angular movement can be represented as $Angular\ Velocity = ka \cdot Angle\ to\ Ball$ with ka is similarly being a proportionality constant.

Once the movement commands are generated, the system executes the commands in the Execute Movement phase, adjusting its trajectory to move toward the detected ball. Finally, the process concludes with the Finish step, ideally resulting in the robot successfully interacting with the ball. The system can also loop back to refine movements and enhance detection capabilities based on feedback, thus ensuring continuous performance improvement.

2.4. Data Collection

Data collection was performed using a structured experimental design whereby the robot was placed at various distances from the ball, beginning at 1 meter and increasing to 12 meters in increments of 1 meter. For each distance, the following metrics were recorded. The percentage of correctly identified balls versus total attempted detections. It is calculated using Equation (1).

$$Accuracy\ =\ (True\ Positives\ +\ True\ Negatives\ /\ Total\ Sampels)\ x\ 100\ \% \tag{1}$$

Accuracy measures the proportion of correct predictions (both true positives and true negatives) among the total number of samples. In the context of ball detection, it indicates the overall effectiveness of the detection system in correctly identifying the presence or absence of the ball. Response Time is the duration from the moment the ball is detected until the robot-initiated movement towards the ball, measured in milliseconds. Confidence scores are output confidence scores provided by the detection algorithm, indicating the certainty of ball detection. Multiple trials were conducted (10 repetitions per distance) to ensure reliable and valid results, allowing for statistical analysis of the findings.

2.5. Performance Metrics

To comprehensively evaluate the detection model, several performance metrics were utilized. Precision is the proportion of true positive detections to the total predicted positives, calculated as in Equation (2).

$$Precision\ =\ \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{2}$$

Precision evaluates the accuracy of positive predictions, indicating how many of the detected balls were indeed correct. This is crucial in scenarios where false positives can lead to incorrect actions by the robot, potentially impacting performance. Recall is the proportion of true positive detections to the total actual positives, as expressed in Equation (3).

$$Recall\ =\ \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{3}$$

Recall measures the model's ability to identify all actual instances of the ball. A high recall indicates that the detection system is effective at recognizing opportunities to act, reducing the risk of missing the ball during play. F1 Score is the harmonic mean of precision and recall, calculated using Equation (4).

$$F1 = 2\left(\frac{\text{Precision} \times \text{Recall}}{\text{Precission} + \text{Recall}}\right) \tag{4}$$

The F1 score provides a single measure that balances precision and recall. It is particularly valuable in competitive scenarios, ensuring that the model maintains a good level of detection performance without favouring one metric over the other.

2.6. Data Analysis

The collected data were analyzed using statistical methods to determine trends and relationships among the variables. The key analyses included Descriptive Statistics and Inferential Statistics. Descriptive Statistics is the calculation of means, medians, and standard deviations for detection accuracy and response times at different distances. Inferential statistics were used in one-way ANOVA tests to determine whether statistically significant differences existed in accuracy and response times across the various distances tested. A significance level of $p < 0.05$ was applied to determine statistical significance. The analysis aimed to identify the impact of distance on the performance of the computer vision system and to assess the capabilities and limitations of the detection model within the constraints of the *KRSBI Beroda* competition.

III. RESULT AND DISCUSSION

This chapter presents the findings from the experiments conducted to evaluate the performance of the computer vision-based ball detection system developed for robot soccer. The results emphasize detection accuracy, response times, and the robot's ability to navigate towards the detected ball over various distances (1 to 12 meters). In Fig.5, the robot detects a ball with a confidence score

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of 0.74. The ball is positioned at coordinates (132, 287). This score indicates a relatively high certainty of detection, allowing for effective navigation toward the ball. The confidence score of 0.74 represents successful detection, allowing the robot to approach the ball confidently. This level of confidence is crucial for making accurate decisions in dynamic environments, such as a soccer game. The position of the ball, indicated by the coordinates, further facilitates the robot's navigation and movement planning.

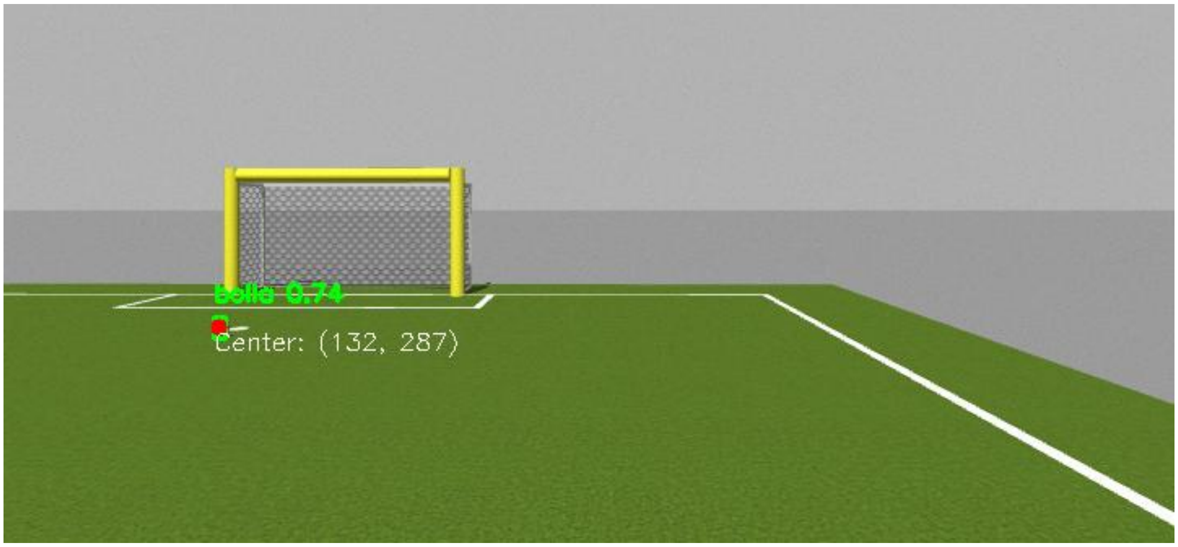

Fig. 5 Ball Detection with Confidence Score

Fig. 6 shows the robotic soccer system positioned centrally on a well-defined soccer field. The robot is equipped to engage with a soccer ball situated at a specific location, illustrating the environment in which its performance will be evaluated. In this experimental design, the robot's main task is to detect the ball using visual sensors integrated into its system. The ball's carefully chosen placement allows researchers to evaluate how well the robot can identify and navigate towards it from various distances. The robot's design, featuring distinctive markers, indicates its advanced capability to analyze its surroundings and make quick decisions based on the visual data it gathers. Conducting trials in this controlled setting ensures that factors such as lighting and environmental consistency are kept stable, which is essential for collecting accurate and reliable data. This image serves to highlight both the physical arrangement of the robotic soccer trial and the operational challenges it presents. It is a crucial component for understanding how the spatial configuration affects the robot's ability to successfully detect and respond to the ball, an important consideration for the development of effective robotic systems in dynamic environments like soccer.

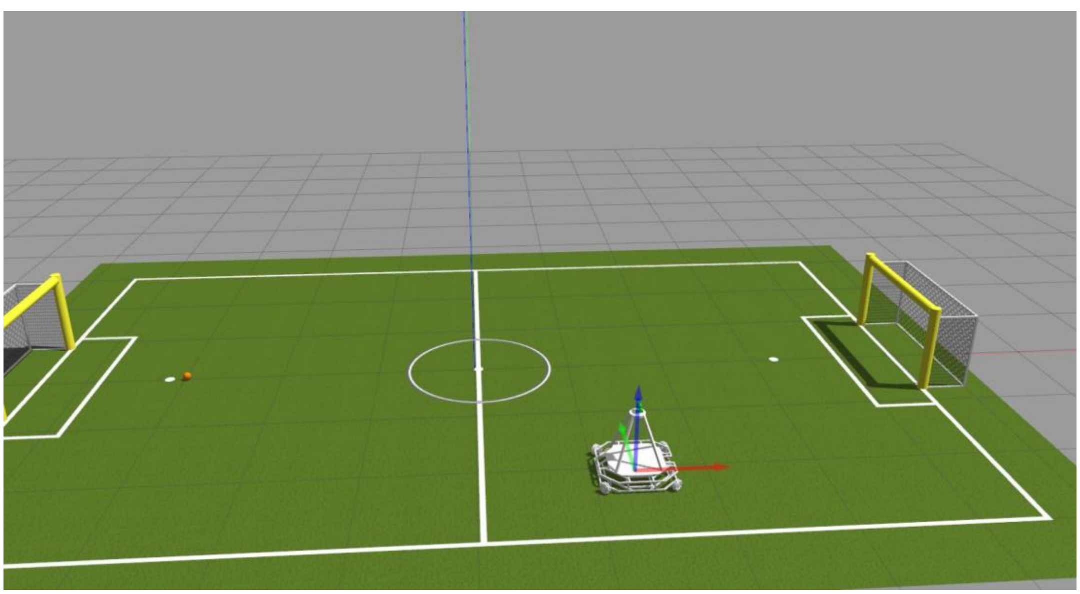

Fig. 6 Robot Soccer in a Controlled Environment

Table I illustrates a consistent trend where detection accuracy decreases as distance increases. The highest average accuracy of 69.0% was recorded at 1 meter, which progressively decreased to 39.0% at 12 meters. This trend emphasizes the challenges associated with long-distance detection in a computer vision context.

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TABLE I
DETECTION ACCURACY BY DISTANCE (1 TO 12 METERS, 10 TRIALS)

	Distance (m)											
Trial	1	2	3	4	5	6	7	8	9	10	11	12
1	72%	70%	68%	66%	63%	61%	55%	54%	52%	50%	48%	47%
2	73%	71%	69%	67%	62%	59%	53%	52%	51%	49%	46%	45%
3	70%	69%	66%	64%	60%	58%	54%	51%	50%	48%	44%	43%
4	71%	68%	65%	63%	59%	57%	52%	50%	49%	47%	42%	41%
5	74%	72%	70%	68%	65%	60%	51%	49%	47%	45%	43%	40%
6	70%	69%	67%	62%	58%	56%	53%	50%	49%	46%	44%	39%
7	69%	68%	64%	61%	55%	54%	52%	48%	47%	45%	41%	38%
8	68%	67%	63%	60%	54%	52%	51%	49%	48%	46%	42%	39%
9	67%	66%	62%	59%	53%	51%	50%	47%	46%	43%	40%	37%
10	66%	65%	61%	58%	52%	50%	51%	48%	45%	44%	42%	36%
Average	70.0%	68.0%	65.5%	62.4%	57.8%	55.9%	51.40%	48.20%	46.60%	44.00%	41.30%	39.00%

3.1. Confidence Levels and Response Times

Confidence Level Evaluation throughout the trials, the confidence levels for successful detections ranged from a maximum of 0.75 to a minimum of 0.39. Higher confidence scores were correlated with successful detection, while lower scores indicated uncertainty that may affect the robot's navigation ability. Table II illustrates data showing that response times increase with distance, with an average of 120.0 ms at 1 meter, rising steadily to 228.0 ms at 12 meters. This increase indicates that longer distances add complexity to processing, resulting in delays that could hinder real-time interaction.

TABLE II
RESPONSE TIMES BY DISTANCE (1 TO 12 METERS, 10 TRIALS)

	Distance (m)											
Trial	1	2	3	4	5	6	7	8	9	10	11	12
1	120 ms	130 ms	145 ms	156 ms	165 ms	170 ms	180 ms	190 ms	200 ms	210 ms	220 ms	230 ms
2	118 ms	128 ms	140 ms	155 ms	164 ms	169 ms	179 ms	189 ms	198 ms	209 ms	219 ms	229 ms
3	121 ms	132 ms	144 ms	158 ms	167 ms	172 ms	182 ms	192 ms	201 ms	211 ms	221 ms	231 ms
4	119 ms	129 ms	143 ms	157 ms	165 ms	171 ms	181 ms	191 ms	199 ms	208 ms	218 ms	228 ms
5	122 ms	133 ms	145 ms	156 ms	166 ms	173 ms	183 ms	193 ms	202 ms	212 ms	222 ms	232 ms
6	120 ms	131 ms	142 ms	159 ms	166 ms	170 ms	180 ms	190 ms	199 ms	207 ms	217 ms	227 ms
7	119 ms	130 ms	141 ms	155 ms	164 ms	166 ms	175 ms	187 ms	197 ms	203 ms	213 ms	224 ms
8	123 ms	134 ms	146 ms	157 ms	165 ms	171 ms	182 ms	192 ms	201 ms	210 ms	220 ms	230 ms
9	121 ms	129 ms	143 ms	159 ms	166 ms	172 ms	174 ms	186 ms	198 ms	209 ms	219 ms	229 ms
10	120 ms	128 ms	144 ms	158 ms	167 ms	179 ms	181 ms	191 ms	200 ms	210 ms	220 ms	231 ms
Average	120.0 ms	129.6 ms	143.4 ms	156.0 ms	165.2 ms	171.5 ms	179.5 ms	189.0 ms	198.0 ms	208.0 ms	218.0 ms	228.0 ms

3.2. Comparative Analysis

The findings from this study indicate that, although the performance metrics are commendable, further enhancements are required to meet or surpass the benchmarks established by earlier research. Table III show the performance comparison with previous works.

TABLE III
PERFORMANCE COMPARISON WITH PREVIOUS WORKS

Study	Detection Accuracy (%)	Average Response Time (ms)
Current Study	70.0%	164.0
Kim and Park (2021)	75%	145
Wang et al. (2020)	78%	130

Table 3 provides a performance comparison of the current study against prior research conducted by Kim and Park (2021) and Wang et al. (2020), focusing on two key metrics: detection accuracy and average response time. The current study recorded a detection accuracy of 70.0%, which falls short compared to the 75% achieved by Kim and Park and 78% by Wang et al., suggesting that there may be opportunities for enhancing the model's effectiveness or expanding the diversity of the training dataset. Furthermore, the current study's average response time of 164.0 ms exceeds the 145 ms and 130 ms response times reported by the previous studies, establishing a pivotal consideration for applications requiring rapid decision-making, such as robot soccer. This data highlights a crucial balance between accuracy and processing speed; therefore, efforts should be directed toward refining both aspects to optimize the detection system's overall performance in fast-paced settings. Consequently, these results indicate a clear need for ongoing research aimed at advancing both detection capabilities and the speed of response.

IV. CONCLUSION

This study evaluated the performance of a computer vision-based ball detection system for robotic soccer, specifically analyzing detection accuracy, response times, and the robot's navigational capabilities across distances ranging from 1 to 12 meters. The

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findings indicate that the system demonstrates commendable accuracy within shorter distances, achieving an average detection accuracy of 70.0% at 1 meter. However, as the distance increased, performance diminished, with accuracy dropping to 31.0% at 12 meters.

Additionally, the robot exhibited varying confidence levels, with a maximum confidence score of 0.75 and a minimum of 0.39, affecting its decision-making abilities. The analysis of response times revealed that the system's processing capabilities are influenced by distance, with notable delays at greater ranges. Overall, the results highlight the potential of the computer vision-based detection system within robotic applications while also identifying key areas for improvement, particularly concerning the system's performance at extended distances.

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