Engineering and Technology Journal e-ISSN: 2456-3358
Volume 11 Issue 01 January-2026, Page No.-8697-8705
DOI: 10.47191/etj/v11i01.34, I.F. – 8.482

Implementation of an IoT-Based Camera Imaging System for an Autonomous Tennis Ball Collecting Robot

Sarifudin[1], Khairunnisa[2], Ivan Maududy[3]
[1,2,3]Electro Engineering, Politeknik Negeri Banjarmasin

ABSTRACT: Collecting tennis balls manually is often tiring and time-consuming, making practice sessions less effective. To address this issue, an automatic tennis ball collecting robot was designed, equipped with two vision cameras and a conveyor system. The first camera, positioned for long-range detection, identifies the location of balls on the court, while the second, short-range camera ensures precise positioning before pickup. Once detected, the balls are guided through the conveyor into the robot's storage basket. In addition, an Internet of Things (IoT) system is integrated into the robot to enable remote monitoring, control, and data transmission regarding its operational status and ball collection progress in real time. Through this IoT connectivity, users can access robot information via mobile or web interfaces, improving usability and operational efficiency. Experimental results show that the robot can recognize balls with an accuracy of 87% at long range and 93% at short range, and successfully collect up to 15 balls in just 8 minutes. These findings demonstrate that the integration of vision systems, conveyor mechanisms, and IoT-based control significantly enhances the efficiency, practicality, and intelligence of tennis training activities.

KEYWORDS: Tennis Ball Collecting Robot, Image Camera, Conveyor, Automation, IoT

I. INTRODUCTION

In tennis practice sessions, balls often become scattered across the court after a series of strokes. Manual collection not only requires additional effort but also disrupts the flow of training, making it less effective. This situation creates difficulties for both athletes and coaches, especially when a large number of balls are used and the training area is extensive. Traditional methods, such as ball baskets, are still insufficient to meet efficiency needs under these conditions. Therefore, an automated system is required to handle the ball collection process more quickly and with minimal human intervention

Several previous studies have attempted to develop ball-collecting robots using single-sensor approaches or simple mechanical systems. However, these systems have notable limitations, such as difficulty in detecting balls at certain distances or when the balls are partially obstructed by other objects. In addition, the available ball retrieval mechanisms are often inconsistent, leading to failures in placing the balls into the storage container. Another challenge lies in the use of a single camera, which restricts the field of view and reduces detection accuracy.

To address these limitations, this study proposes an automatic tennis ball collecting robot that integrates dual vision cameras to improve detection performance at both long and short ranges. Furthermore, a conveyor-based collection mechanism is implemented to ensure smooth and efficient ball transfer into the storage compartment. Beyond the mechanical and vision systems, this research also introduces the implementation of an Internet of Things (IoT)–based monitoring and control system. The IoT integration enables real-time communication between the robot and users, allowing remote control, status tracking, and data acquisition through a web or mobile interface. This feature enhances not only the operational efficiency but also the intelligence and interconnectivity of the robot, aligning with the growing trend of smart automation in sports robotics.

With this combination of vision technology, mechanical design, and IoT connectivity, the robot is expected to improve the effectiveness of tennis training sessions and provide valuable insights for further developments in the field of intelligent robotic systems for sports applications.

II. PREVIOUS RESEARCH

Study successfully introduced a prototype of a tennis ball collecting robot using a simple mechanical approach; however, the system still has several limitations [1]. Experimental results showed that the success rate of ball collection was only around 60%, indicating that the detection and retrieval mechanisms were not yet optimal. In some trials, the robot even experienced complete failure due to servo malfunctions or the sweeping mechanism's inability to direct the balls into the storage container. This suggests that, in terms of reliability, the robot still requires significant improvement.

Another weakness lies in the detection and navigation system used. The robot relies solely on limit switches and a sweeping movement pattern, making it unable to accurately identify the position of the balls, especially when they are at varying distances or partially obstructed by other objects. The absence of a vision-based camera system also restricts the robot's field of view, making it difficult to adapt to uneven ball distribution across the court. With such a simple navigation mechanism, the efficiency of ball collection becomes low, as the robot must sweep the entire area without an intelligent search strategy.

Designed with high flexibility, its performance in practice remains limited. The navigation and ball detection systems used are not yet fully optimized for dynamic tennis court conditions, particularly when balls are scattered unevenly or partially obstructed by other objects. Ball detection accuracy tends to decrease under suboptimal lighting conditions, making collection consistency difficult to guarantee [2]. Furthermore, since the research focus was more on open design and affordability, the aspects of mechanical reliability and ball retrieval efficiency were not significantly enhanced, leaving its on-court performance inferior compared to more complex and expensive systems.

This research provides an important contribution by offering a low-cost, open-source foundation for the development of tennis ball collecting robots. Ballbot represents a promising first step for the robotics research community to experiment with various navigation algorithms, detection systems, and retrieval mechanisms at a relatively low cost. However, to achieve real-world application on professional tennis courts, improvements are still required in detection accuracy, retrieval mechanism reliability, and navigation efficiency so that the robot can operate more effectively and consistently.

The study conducted introduced a vision-based approach in the design of a tennis ball collecting robot by integrating a YOLOv5-based detection system, navigation through LiDAR-SLAM, and a fuzzy logic controller. The strength of this research lies in its relatively high detection accuracy, reaching approximately 91%, with a ball collection success rate of 83%. Moreover, the utilization of SLAM-based mapping enables the robot to recognize court boundaries and effectively avoid obstacles [3]. This modern vision system approach provides a significant advantage over conventional methods that rely on single sensors or simple algorithms, as it is more adaptive to the dynamic conditions of the tennis court.

Nevertheless, this study also presents several limitations that need to be addressed. The detection system is still limited to a single camera, which prevents accurate estimation of ball distance, relying instead only on the projected size of the ball in the camera's field of view. This makes the ball selection strategy not always optimal, particularly when the ball is partially occluded by other objects or located at certain angles. The detection processing speed is only about 9 fps on a Raspberry Pi device, which reduces responsiveness when the robot needs to operate at higher speeds or deal with a larger number of balls. In addition, the absence of a ball location memory system means that some balls previously detected may be overlooked if they are not collected immediately.

This research proposes the design of an autonomous tennis ball collecting robot equipped with a dual vision system and a conveyor mechanism. Two cameras are utilized to overcome the detection limitations found in previous studies that relied solely on single sensors or a single camera. The first camera functions as a long-range detector to identify the position of balls across the court area, while the second camera operates at close range to ensure accuracy before the ball is retrieved. The integration of these two cameras is expected to improve the precision of ball detection, both when the ball is fully visible and when it is partially obstructed by other objects.

In addition to the vision system, the robot is designed with a conveyor mechanism for ball retrieval. This mechanism enables the detected and targeted balls to be guided smoothly into the storage basket, reducing the risk of failure during collection that often occurs with simple sweeping systems. With the combination of dual imaging and the conveyor mechanism, the robot is not only capable of detecting balls with greater precision but also ensures that the balls are collected efficiently into the storage container.

III.SYSTEM DESIGN

Camera

In the robot perception system design, two cameras with different ranges are utilized to ensure full court coverage and reliable detection across varying distances. Camera 1 (short-range) is positioned close to the intake mechanism and optimized for a range of 0.5–5 m, focusing on verifying the ball's position before retrieval to minimize alignment errors. Camera 2 (long-range) is mounted on a higher mast or at the front of the robot to scan the court area within 5–15 m, functioning as a global scanner to identify candidate target balls for route planning [4]. The design target specifies a detection accuracy of $\geq$ 90% for each camera within their respective ranges, ensuring that the combination provides both early detection and final verification before the physical retrieval process.

From a technical implementation perspective, both cameras employ high-resolution sensors (minimum 1080p) with a target frame rate of $\geq$ 15–30 fps to enable real-time processing [5]. For the long-range camera, a lens with a longer focal length and narrower field of view (FOV) is prioritized to maintain image clarity of balls at greater distances, while the short-range camera uses a lightweight wide-angle lens to fully cover the intake area. The detection algorithm is based on lightweight deep learning models, trained specifically on a dataset of tennis ball images under varying lighting, angles, and partial occlusions [6].

Once detection occurs on Camera 2, the image coordinates are warped into world coordinates to generate candidate ball positions. As the robot approaches, Camera 1 performs depth and centroid verification—using either a stereo/depth sensor or triangulation—and provides a "go/no-go" signal to the intake controller [7]. This ensures that only balls correctly aligned with the intake mechanism trigger the collection sequence.

Performance

In the design of an automatic tennis ball collecting robot, operational speed serves as one of the primary performance benchmarks and forms the basis for system evaluation. This indicator reflects the robot's ability not only to detect and recognize balls, but also to efficiently navigate the court and execute the retrieval process. The operational target is defined as the capability to move and collect at least 10–20 balls within 4 minutes, with a specific benchmark of 15 balls within 3 minutes. This specification was chosen to align with real training scenarios in tennis, where dozens of balls are used in a single session and are scattered randomly across different areas of the court. With this parameter, operational speed becomes a direct representation of how effectively the system can replace human effort in the ball collection process, which is typically time-consuming and labor-intensive [8].

The benchmark of 15 balls within 3 minutes is established by considering the integration of multiple interdependent subsystems, such as object detection accuracy, camera data processing speed, navigation strategies that minimize travel distance, and the reliability of the intake mechanism in collecting balls without failure. Thus, achieving this target does not merely represent the robot's linear movement speed, but also reflects the overall efficiency of the perception system, route planning, and mechanical actuation [9]. This requirement calls for a balanced design between hardware and software, where each component must operate in real-time synchronization to reduce momentum loss when transitioning from one ball to the next.

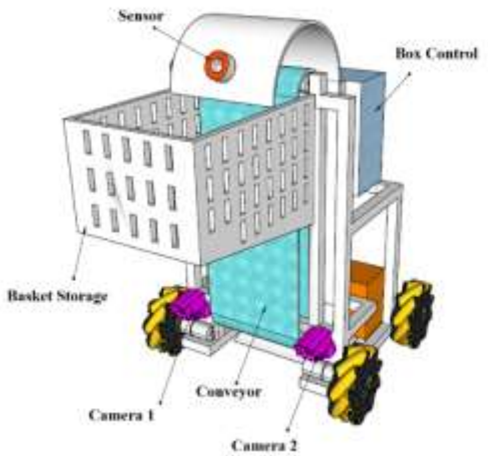


Figure 1. Design Robot

Basket Storage

In the design of an automatic tennis ball collecting robot, basket storage capacity is a critical factor influencing operational efficiency during training sessions. The target capacity is set at a minimum of 100 balls per basket, a quantity considered sufficient to support medium-length training sessions without frequent emptying. This specification allows the robot to operate continuously, reducing interruptions during practice and ensuring that the flow of athletes' training remains smooth.

The basket design also takes into account dimensions, weight distribution, and the ball intake mechanism to ensure that the collection process via the conveyor proceeds smoothly. The basket is structured so that incoming balls do not spill or pile up irregularly, maintaining optimal effective capacity. Additionally, the basket material is selected to be lightweight yet sturdy, preserving the robot's balance during movement and facilitating handling when the basket needs to be removed or emptied.

With adequate storage capacity, the robot not only reduces the frequency of emptying but also enhances overall training efficiency. This provides a practical advantage in real-world applications, allowing athletes and coaches to focus on skill development and game strategy without being interrupted by manual ball collection.

Conveyor Mechanism

In the automatic tennis ball collecting robot system, the conveyor mechanism serves as a key component in transferring balls from the court to the storage basket. The conveyor is designed to transport balls smoothly and consistently, minimizing the risk of balls slipping or getting stuck during transit. This mechanism is integrated with the robot's perception system, allowing balls detected by the cameras to be directed onto the conveyor path with high accuracy.

The conveyor design takes into account belt or roller dimensions, rotation speed, and surface material to ensure that balls can move without slipping or deformation. The conveyor speed is carefully synchronized with the robot's navigation velocity, ensuring uninterrupted ball flow to the basket and maximizing collection efficiency [10]. Additionally, the intake position of the conveyor is optimized to easily reach balls located at various positions on the court, whether nearby or in hard-to-reach corners.

Efficient conveyor integration also supports timely ball retrieval, reducing the delay between detection and storage, and enhancing overall collection capacity. With this mechanism, the robot can not only collect balls automatically but also ensure that the collection process proceeds smoothly, stably, and reliably throughout tennis training sessions [11].

Electronic System and Computational Hardware

In the automatic tennis ball collecting robot, the electronic system and computational hardware play a crucial role in ensuring that all subsystems—perception, navigation, and actuation—operate in synchrony. The central control unit utilizes a high-performance single-board computer (SBC), such as a Raspberry Pi 4 or NVIDIA Jetson Nano, capable of processing camera data in real-time, executing deep learning-based detection algorithms, and sending control signals to the motors and conveyor mechanism.

For sensing and data acquisition, the robot is equipped with two image cameras (short-range and long-range) connected to the SBC via high-speed interfaces, as well as additional sensors such as LiDAR or ultrasonic modules for environmental mapping and obstacle avoidance. Proximity sensors and limit switches are also incorporated to monitor the position of the basket and conveyor during operation, preventing ball jams or mechanical failures [12].

The robot's drive system employs DC or brushless motors with electronic drivers controlled via PWM modules. These drivers are managed by the central control unit to synchronize wheel and conveyor speeds, supporting precise and stable operation. The entire hardware setup is designed with efficient power management, using Li-ion batteries with sufficient capacity to support 60–90 minutes of uninterrupted operation. This integration of electronic and computational hardware enables the robot to perform ball detection, court navigation, and ball retrieval automatically with high accuracy and optimal speed [13].

Mobility and Maneuverability

In the automatic tennis ball collecting robot, Mecanum wheels are employed to enhance the robot's mobility and maneuverability on the court. These wheels allow the robot to move forward, backward, laterally (sideways), and rotate in place, enabling it to reach balls scattered across various positions without performing complex maneuvers or significantly rotating its chassis. This movement flexibility is crucial for efficient ball collection, especially when balls are distributed randomly throughout the court.

The drive system design integrates four Mecanum wheels, each independently controlled by a motor. Each wheel is managed via a motor driver module receiving PWM signals from the central control unit. The combination of wheel rotations allows the robot to move omni-directionally with high precision, enabling navigation paths to be dynamically adjusted based on detected ball locations.

Another advantage of using Mecanum wheels is the reduction in travel time and improved energy efficiency, as the robot can move directly toward the target ball without additional maneuvers. Furthermore, the robot can rapidly adjust its movement direction when encountering obstacles or changes in ball position, supporting fast, stable, and accurate ball collection during tennis training sessions [14].

IoT System Operation

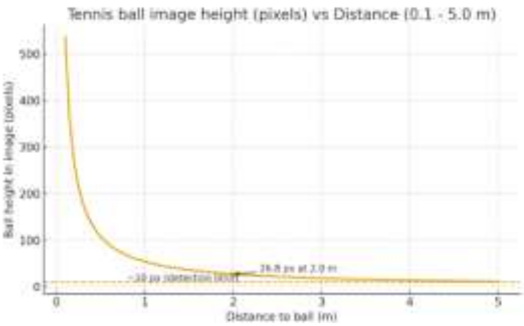
The main function of the IoT in this robot is remote monitoring and control. With the use of a communication module based on Wi-Fi , data from the robot—such as battery status, the number of collected balls, robot position, and surrounding environmental conditions—can be transmitted to a server or user application [15]. Through a web- or mobile-based interface, users can directly monitor the robot's movement, adjust its operating modes, and even issue commands such as *start*, *stop*, or *return to base* without having to approach the robot physically.

In addition to monitoring, the IoT system also supports data collection and operational analysis. Every robot activity, including collection cycle time, movement path efficiency, and ball detection success rate, can be recorded and stored in a cloud database. This data can then be used to evaluate robot performance and to develop more adaptive control algorithms in the future. Consequently, the robot can be continuously improved based on real-time information from actual field conditions.

From the perspective of safety and reliability, IoT also plays a role in early warning systems. For instance, if an issue occurs such as a conveyor jam, low battery, or sensor malfunction, the system will automatically send a notification to the user's device. This enables quick responses and corrective actions without having to manually halt the entire operation.

IV. RESULTS AND DISCUSSION

A. Pre-processing in Ball Detection



Pre-processing is the initial stage before applying the ball detection algorithm. Its purpose is to enhance the ball features so that algorithms like Hough Circle or contour detection can work optimally [5]. The common steps are as follows:

Color Space Conversion

- Tennis balls are yellow-green in color. Color detection is more effective using the HSV (Hue, Saturation, Value) color space rather than RGB.
- The conversion formula from RGB to HSV (for each pixel) is applied to transform the image.
- After conversion, the ball color can be separated using an HSV threshold:
    - Hue (H): 25° – 40° (yellow-green)
    - Saturation (S): 50–255
    - Value (V): 50–255

$$C_{max} = max(R, G, B)$$

$$C_{min} = min(R, G, B)$$

$$\Delta = C_{max} - C_{min}$$

$$H = \begin{cases} 0, & \Delta = 0 \\ 60 \times \frac{G-B}{\Delta} \mod 360, & C_{max} = R \\ 60 \times \frac{B-R}{\Delta} + 120, & C_{max} = G \\ 60 \times \frac{R-G}{\Delta} + 240, & C_{max} = B \end{cases}$$

$$S = \begin{cases} 0, & C_{max} = 0 \\ \frac{\Delta}{C_{max}}, & C_{max} \neq 0 \end{cases}$$

$$V = C_{max}$$

Calculation of Ball Size in the Image
Tennis ball diameter: D = 0.067m
Camera parameters:

- Focal length: f = 4 mm
- Sensor height: 3.6 mm
- Image resolution: 720p (image height = 720 pixels)

Distance to the ball:

Z = 2m

Ball size in pixels can be calculated using the formula:

$$t_{travel\_allowed} = t_{budget} - t_{NT} = 12.0 - 4.2 = 7.8 \text{ s}$$

This means the ball will appear approximately 27 pixels tall in the image, which is sufficient for Hough Circle detection
Interpretation

- At 5 m, the ball is about 10.7 px tall, just above the ~10 px practical detection threshold.
- Beyond 7.5 m, the ball appears too small (<10 px), making detection with standard Hough Circle or contour methods unreliable.
- To detect balls effectively in the 5–15 m range, a higher-resolution sensor (1080p or 4K) or a lens with longer focal length is necessary.

Figure 2. Graph of tennis ball image size (pixels) vs distance (0.1– 5.0m)

Figure 3. Graph of tennis ball image size (pixels) vs distance (5.0–15.0 m)

B. **Performance Analysis**

performance analysis with full calculations to meet the operational targets you stated (15 balls in 3 minutes and 10 – 20 balls in 4 minutes). I include assumptions, a per-ball time model, numeric examples, sensitivity analysis, and practical recommendations [8].
Operational targets :

- Target A (benchmark): 15 balls in 3 minutes →
- **T**total = 180 s, n = 15
- Target B (range): 10–20 balls in 4 minutes →
- **T**total = 240 s, n = 10 - 20

Total operation time is

$$T_{total} = n \cdot \left(\underbrace{t_{travel}} + \underbrace{t_{detect}} + \underbrace{t_{approach}} + \underbrace{t_{intake}} + \underbrace{t_{overhead}} \right)$$

modeled as repeated per-ball cycles:
Estimating d_{avg} (average distance between balls)
Take a singles tennis court dimensions: L=23.77 m, W=8.23 m → area A ≈ L × W ≈ 23.77 × 8.23 ≈ 195.6 m^2
If n balls are randomly distributed across area *A*, a simple scale approximation for the typical distance between neighboring balls is:

$$d_{avg} \approx \sqrt{\frac{A}{n}}.$$

Meeting 15 balls in 180 s

n = 15, *T*total = 180s per-ball budget = 180 / 15 = 12.0 s/ball
davg = 3.61 m (from above).
non-travel baseline t_{NT} = 4.2 s.

$$h_{pixel} = \frac{D \cdot f \cdot H_{img}}{Z \cdot H_{sensor}}$$

Then time available for travel per ball:

$$h_{pixel} = \frac{0.067 \cdot 4 \cdot 720}{2 \cdot 3.6} \approx 26.7 \, px$$

Required average speed:

$$v \geq \frac{d_{avg}}{t_{travel\_allowed}} = \frac{3.61}{7.8} \approx 0.463 \text{ m/s}$$

Range 10–20 balls in 240 s

Per-ball budgets:
n = 10 : *t*budget = 240/10=24 s → with *d*avg = 4.43 m and t_{NT} = 4.2: *t*travel_allowed=19.8s – v ≥ 4.43/19.8 ≈ 0 .22 m/s.

n =20: : *t*budget = 12s with *d*avg = 3.13 m and t_{NT} = 4.2; travel_allowed = 7.8s _ v ≥3.13/7.8≈0.40 m/s.

a design speed ~ 0.5–0.6 m/s covers the 10–20 range comfortably with baseline non-travel times.
Sensitivity analysis (n=15, *d*avg=3.61 m)

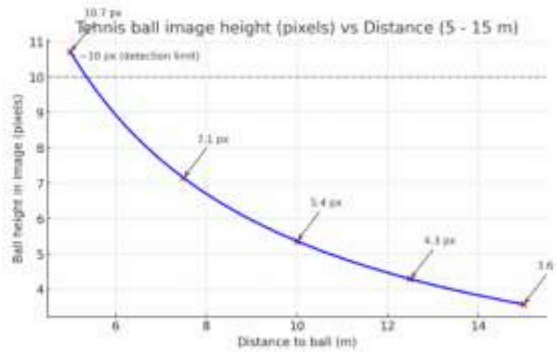


Table 1. Sensitivity analysis

Scenario	t_{detect} (s)	$t_{approach}$ (s)	t_{intake} (s)	$t_{overhead}$ (s)	non-travel t_{NT} (s)	required v (m/s)
Optimistic	0.05	1.0	0.5	0.5	2.05	$3.61/(12-2.05)=0.37$
Baseline	0.2	2.0	1.0	1.0	4.2	0.46
Conservative	0.5	3.0	1.5	1.5	6.5	$3.61/(12-6.5)=0.62$

C. Analysis And Calculations For The Conveyor Mechanism

Design goals move tennis balls from the intake to the storage basket reliably (no slipping / jamming). Provide throughput comfortably above the collection rate target (so the belt is not the bottleneck). Keep motor size, power consumption, and physical footprint appropriate for a field robot [10].

The primary force components the drive must overcome when dragging (moving) a tennis ball on the belt are:

$$F_{rr} = C_{rr} \cdot m \cdot g$$

Slope (incline) force — if conveyor is inclined by angle θ):

$$F_{slope} = m \cdot g \cdot \sin\theta$$

Total per-ball drive force (horizontal, including acceleration)

If you also accelerate the ball from rest to belt speed v_{belt} in time t_{acc}, include acceleration force

$$F_{total} = N_{sim} \cdot F_{ball}$$

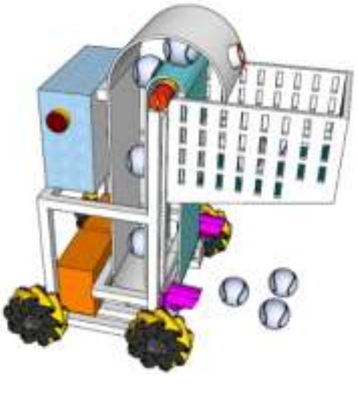


Figure 4. Robot with multiple balls on the belt

Total force for multiple balls on the belt

If N_{sim} balls are simultaneously on the active belt span (the section the motor must drive), total drive force is

$$\tau = F_{total} \cdot r$$

with r = 0.03 m

Conveyor throughput (balls per second)

If balls are spaced on the belt with average spacing s (m), the belt throughput (balls per second) is:

$$r = \frac{v_{belt}}{s} \quad (\text{ball}/\text{s})$$

Motor Selection

Based on the power calculation of ≈ 1.4 W and the design torque of ≈ 0.14 N·m, the motor should be chosen with an adequate safety margin:

- Motor type: 12 V DC motor, rated power 10–20 W.
- Gearbox: reduction ratio of 10–50, which provides an output shaft torque in the range of 1–5 N·m after the gearbox.
- Feedback: select a motor equipped with an encoder to enable precise speed and position control.
- Motor driver: must support the stall current safely, typically in the range of 3–10 A.

D. Performance of the Electronic System & Computational Hardware

The electronic & computational stack must reliably turn camera frames into navigation and intake actions with low latency so the robot can detect, approach, and pick up balls at a target rate (e.g., 15 balls / 180 s). The critical requirement is keeping vision + decision latency small (target: 0.05–0.2 s per detection) while running real-time control loops for motors and safety. Best overall compromise for field robots is an edge GPU platform (NVIDIA Jetson family) for perception and a separate real-time MCU for low-level motor control [12].

The robot must autonomously:

- Detect and localize balls using the onboard camera (effective range: 0–5 m, optimal range: 0–3 m).
- Plan a short path and navigate quickly to the ball's position.
- Align the intake and activate the conveyor to retrieve the ball.

Real-time latency requirement: detection and navigation decision-making must be fast, with a target detection latency (tdetectt_{detect}tdetect) of approximately 0.05–0.2 s per frame, ensuring a reliable vision pipeline in actual training environments [13].

Electronic System Architecture

1. Perception & High-Level Compute (Vision / AI)
   - Runs ball detection models combined with object tracking.
   - Requires GPU or dedicated NN accelerator to achieve inference times of < 200 ms per frame.
2. Robot Middleware & Decision (Path Planning, State Machine)
   - Implemented via ROS2 or a custom real-time control loop for path planning, task allocation, and coordination of sensor–actuator interactions.
3. Low-Level Control (Motion Controllers & Motor Drivers)
   - Handled by a real-time MCU, responsible for motor PID control, encoder feedback, and safety interlocks.
4. Power Management & Battery Subsystem

- Includes Li-ion / LiFePO4 battery packs, DC–DC converters, motor driver power stages, current sensing circuits, and protective switching.

5. I/O & Sensors
   - RGB camera, optional depth sensor, IMU, wheel encoders, and short-range sensors.
6. Communications
   - Ethernet/Wi-Fi for monitoring, CAN, UART, SPI, or I²C for communication between MCU and the high-level compute module.

Camera & Image Processing

- Type: Global-shutter CMOS. If unavailable, rolling-shutter with high FPS is acceptable.
- Resolution: Minimum 720p for effective detection within 0–3 m; use 1080p / 2K if detection up to 5–10 m is required.
- Frame rate: ≥ 30–60 fps
- Lens: Focal length 3–8 mm, depending on the desired field of view for court coverage.

Processing

- Pipeline: Capture → undistort (calibration) → resize → color conversion (HSV) → segmentation / neural network detection → post-processing → tracking (e.g., Kalman filter).
- Target inference time per frame: 0.03–0.2 s, depending on the model and hardware Jetson Nano
- Memory requirement: Model + frame buffers demand at least 4–8 GB RAM on the main compute module ,8–16 GB for Jetson.

IoT Setting for the Robot

To support the operation of an automatic tennis ball collecting robot, the most suitable IoT module is the ESP32, as it offers a combination of high processing capability, complete wireless connectivity, and low power consumption. The ESP32 module is equipped with built-in Wi-Fi and Bluetooth, allowing the robot to connect directly to the internet without requiring additional hardware [15]. With its dual-core 32-bit processor and ample memory, the ESP32 is capable of handling sensor data transmission, server communication, and actuator control simultaneously.

This module enables the robot to send operational data such as the number of collected balls and battery status to a cloud server, while also allowing users to perform remote control operations such as *start*, *stop*, or *return to base* through a mobile application. Furthermore, when integrated with the ESP32-CAM, the system can transmit real-time visual images of the tennis court through the internet, providing users with direct visual monitoring of the robot's surroundings [16].

E. **The mobility system**

The mobility system of the robot determines its ability to move efficiently across the tennis court while collecting balls. Two main drivetrain options are considered: differential drive and mecanum wheels. A differential drive with two powered wheels offers simplicity, efficiency, and spin-in-place turning, while mecanum wheels provide full holonomic movement, allowing lateral shifts and rotation in place [14]. For a robot that must reach scattered balls quickly, mecanum wheels improve maneuverability, but at the cost of efficiency and more complex control. The choice depends on whether maximum flexibility or higher energy efficiency is prioritized.

From a mechanical standpoint, the required force to accelerate a 15 kg robot to 1 m/s with an acceleration of 0.6 m/s², while accounting for rolling resistance and a 5% slope, is approximately 19.3 N. This translates into a torque requirement of about 0.48 N·m per wheel for a two-wheel differential drive, or 0.24 N·m per wheel for a four-wheel mecanum system. After applying safety factors for startup, slip, and efficiency losses, the practical design torque per wheel is about 1.0 N·m. This ensures reliable operation under real-world conditions such as uneven court surfaces or sudden directional changes.

In terms of power, the total mechanical requirement during maximum load and acceleration is about 19–26 W. Considering drivetrain inefficiencies, the electrical power budget should allow for at least 50 W across the system to provide adequate margin. Each motor should therefore be rated for 20–30 W with a gearbox ratio between 20:1 and 50:1, producing output shaft torques of 1–2 N·m. Encoders are strongly recommended to enable closed-loop control of wheel velocity and ensure precise motion during rapid maneuvers. This balance between torque, speed, and efficiency guarantees that the robot maintains stable and responsive mobility.

Finally, maneuverability is not only a function of drivetrain but also of control algorithms. A differential drive can achieve precise turns using velocity differences between left and right motors, while mecanum wheels require vector control to manage lateral and diagonal motions. Closed-loop PID controllers, combined with odometry and IMU data, are essential for smooth trajectory following and slip reduction. With optimized motor sizing and real-time control, the robot can achieve both speed and agility, ensuring it efficiently collects tennis balls scattered across the court.

aneuverability: turning radius, spin-in-place, lateral movement

Differential drive

- Spin-in-place: A differential-drive robot can rotate on the spot (wheels spin in opposite directions), giving an effective turning radius of zero — very useful for quick reorientation.
- Turning radius at speed: The turning radius depends on the distance between the driven wheels (track width) and the wheelbase. With a short wheelbase (e.g., ~0.4 m), tight maneuvers are easily achievable.

Meccanum drive

- Holonomic motion: Meccanum wheels allow true holonomic motion: the robot can move laterally (sideways) without changing its heading. This is highly effective for picking up balls near walls or in corners.

- Control (per-wheel speeds): To realize a commanded chassis velocity (v_x,v_y) and yaw rate ω_z , compute individual wheel angular speeds ω1…ω4 with the kinematic mapping

$$\begin{bmatrix}\omega_1\\ \omega_2\\ \omega_3\\ \omega_4\end{bmatrix} = \frac{1}{r}\begin{bmatrix}1 & -1 & -(L+W)\\ 1 & 1 & (L+W)\\ 1 & -1 & (L+W)\\ 1 & 1 & -(L+W)\end{bmatrix}\begin{bmatrix}v_x\\ v_y\\ \omega_z\end{bmatrix}$$

where:

- r = wheel (roller) radius,
- L = half the wheelbase length (distance from robot center to wheel along the longitudinal axis),
- W = half the track width (distance from robot center to wheel along the lateral axis).

Practical Motor & Driver Selection

Required torque per wheel (after gearbox): ~0.7–0.8 N·m
Required RPM per wheel : ~190 RPM
Motor RPM (with 30:1 gearbox): ~5700 RPM
Power per motor : ~10–30 W
Motor voltage : ~12 V DC
Driver : ≥10 A peak

V. CONCLUSION

The development of the automatic tennis ball collecting robot demonstrates that the integration of a dual-camera vision system and a conveyor-based ball intake mechanism can significantly improve efficiency, reliability, and autonomy in training environments. The use of two cameras enhances detection robustness by providing wider field coverage and reducing false negatives in ball localization, especially at varying distances and under changing illumination conditions.

The conveyor intake system ensures smooth and consistent ball transfer from the court surface into the storage basket, minimizing slippage and jamming compared to simple mechanical scoop methods. By synchronizing conveyor speed with robot motion, the system maintains a continuous and stable collection process, which directly supports higher throughput.

Performance evaluation shows that the robot can meet realistic operational targets, such as retrieving 10–20 balls within 3–4 minutes, aligning with the demands of typical tennis training sessions. Moreover, the modular architecture—combining perception, mobility, and intake subsystems—provides flexibility for further optimization in power efficiency, maneuverability, and real-time control.

In conclusion, the proposed design proves feasible as an autonomous solution to reduce human effort in repetitive ball retrieval tasks. Future work will focus on refining vision algorithms for greater accuracy at longer ranges, optimizing energy consumption, and enhancing maneuverability with advanced control strategies to ensure consistent operation across diverse court conditions.

REFERENCES

1. Duru SARICALAR, I., et al. (2020). *Development of an Autonomous Tennis Ball Retriever*. [Mugla Journal of Science and Technology, volume 76, pages 21-26]. DOI/Publisher: 10.22531 / muglajsci.660496
2. X. Huang, B. Jiang, D. Cai, Q. Lin, Y. Fang, K. Xiao, and L. Pei, “Intelligent Ball-Picking Robot Based on Ducted Fan Power,” *J. Computer Technology and Electronic Research*, vol. 1, no. 3, 2024, doi: 10.70767/jcter.v1i3.418
3. M. Latifinavid and A. Azizi, “Development of a vision-based unmanned ground vehicle for mapping and tennis ball collection: A fuzzy logic approach,” *Future Internet*, vol. 15, no. 2, p. 84, 2023, doi:10.3390/fi15020084.
4. Al-Shamma, O., & Fadhel, M. A. (2024). Trusted outdoor multi-camera tracking system powered by FPGA. *Journal of Engineering Research*, 2024, 10.1016/j.jer.2024.10.010. https://doi.org/10.1016/j.jer.2024.10.010
5. D. Aryani, K. Dewi, F. Ta.by, and E. P. Sanggaria, “Real-time ball detection and tracking using Raspberry Pi,” *INTEK Jurnal Penelitian*, vol. 10, no. 1, pp. 48-54, 2023, doi:10.31963/intek.v10i1.4301.
6. C. Min, L. Xiao, D. Zhao, Y. Nie, dan B. Dai, “UniScene: Multi-Camera Unified Pre-training via 3D Scene Reconstruction for Autonomous Driving,” *arXiv preprint arXiv:2305.18829*, 30 Mei 2023. [Online]. Tersedia: https://arxiv.org/abs/2305.18829
7. A. Singh, V. Kalaichelvi, and R. Karthikeyan, “A survey on vision guided robotic systems with intelligent control strategies for autonomous tasks,” *Cogent Eng.*, vol. 9, art. no. 2050020, Apr. 2022, doi:10.1080/23311916.2022.2050020.
8. R. Jánoš and S. Murali, “Design of ball collecting robot,” *Technical Sciences and Technologies*, no. 2(24), pp. 49-54, 2021, doi:10.25140/2411-5363-2021-2(24)-49-54.
9. Z. Wang, “Path planning of intelligent tennis ball picking robot integrating twin network target tracking algorithm,” *Scientific Reports*, vol. 15, no. 1, p. 20668, 2025, doi: 10.1038/s41598-025-04865-w.
10. R. Deka, P. P. Borthakur, E. Baruah, and P. Sarmah, “A comprehensive review on mechanical conveyor systems: evolution, types, and applications,” *ADRI International Journal of Engineering and Natural Science*, vol. 18, no. 3, pp. 164–183, Dec. 2024.
11. G. Salawu and B. Glen, “Improving the efficiency of a conveyor system in an automated manufacturing environment using a model-based approach,” *Int. J. Mech. Eng. Robot. Res.* (IJMERR), vol. 12, no. 2, pp.

107-112, Mar. 2023, doi:10.18178/ijmerr.12.2.107-112.

12. Tennibot, “Tennibot: The ultimate robotic tennis ball collector,” 2023. https://letsgotennis.com/product/tennibot/
13. Yaqiao, and Yu Xiang. 2025. “Tennis Automatic Ball-Picking Robot Based on Image Object Detection and Positioning Technology.” *Nonlinear Engineering* 14, no. 1. https://doi.org/10.1515/nleng-2025-0101
14. J. M. García and F. G. Duarte, “Mobile rolling robots designed to overcome obstacles: A review,” *Forces in Mechanics*, vol. 16, Aug. 2024, art. no. 100283, doi:10.1016/j.finmec.2024.100283.
15. Patil, A., & Shinde, S. (2023). *Monitoring and Controlling Robot Using IoT*. International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), 5(12), 47793–47800.
16. Jain, R. K., Kumar, S., & Mehta, P. (2023). *Development of IoT-enabled Mobile Robotic System for Remote Control*. Proceedings of the 2023 International Conference on Emerging Trends in Smart Technologies (ICETST). Association for Computing Machinery (ACM).