Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Machine Learning-Based Ball Throwing Machine: An Intelligent Approach to Precision and Adaptability

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ARTICLE INFO

Received: 30 Dec 2024

Revised: 05 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

Sports training and industrial settings have made extensive use of automated ball-throwing machines; however, conventional models' precision and adaptability are limited by their fixed mechanical parameters. This study introduces a novel machine learning-based ball-throwing system that uses AI-driven decision-making and real-time sensor data to dynamically modify its throwing parameters. To maximize accuracy, the system's three components—a Ball Propelling Unit (BPU), a Hydraulic Pitching Assembly (HPA), and a Computer Imaging Device (CID)—work together. Equipped with a gyroscope, LIDAR, and a PIXY2 camera, the CID uses machine learning algorithms to determine the best course, detect user position, and identify coloured patches for tracking. The BPU improves ball swing and trajectory stability by imparting controlled spin through a Rifled Barrel (RB) that is slew motor-controlled. The HPA provides the necessary force, dynamically adjusting it according to AI-predicted values. It is made up of a hydraulic pump, hydraulic valve, and hydraulic cylinder. The machine learning framework combines reinforcement learning to continuously improve accuracy through real-time feedback and supervised learning to evaluate historical throwing data. The system's self-adjusting capability, which lowers error margins and guarantees constant throwing accuracy, is demonstrated by experimental evaluations. With its intelligent and adaptable pitching experience, the suggested machine has a lot of potential for use in recreational and sports training environments. Potential future developments could concentrate on improving response time, extending machine learning algorithms, and adding real-time feedback systems.

Keywords: Machine Learning, Ball Throwing Machine, Computer Vision, Hydraulic Pitching Assembly, Ball Trajectory Prediction, User Identification, Sports Training, Raspberry Pi, Pixy2 Camera, Motion Control.

INTRODUCTION

In order to automate throwing mechanisms for training, simulation, and material transportation, ball-throwing machines have been used extensively in both industrial and sports settings. Conventional machines are limited in their ability to adjust to changes in the real-time environment, such as changing distances [1], wind conditions, or user positioning, because they are dependent on predetermined mechanical parameters. Because of these restrictions, throws are inconsistent, which lessens their usefulness in real-world situations. Developments in machine learning (ML) and artificial intelligence (AI) have made it possible to create flexible robotic systems that can self-learn and adjust motion parameters in real time. Machine learning has been essential to robotics and automation in recent years, allowing systems to adjust to changing environmental conditions, fix mistakes, and increase efficiency. [2] Conventional sports training ball-throwing devices, like those used in baseball, cricket, and tennis, usually function according to pre-set

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Research Article

launch parameters. These devices work well for repetitive practice, but they are unable to dynamically modify throws in response to user feedback in real time. [3] Similar to this, ball-throwing mechanisms are employed in industrial settings for projectile delivery and material handling systems where it is crucial to be able to adjust to varying weights, distances, and target accuracy.

In order to improve throwing accuracy, this study presents a machine learning-based ball-throwing device that makes use of computer vision, sensor-based feedback, and AI-driven trajectory adjustments. [4] In order to modify launch parameters like force, angle, and spin, the system dynamically evaluates the user's position, distance, and throwing circumstances. Higher precision and dependability are ensured by the system's continuous performance improvement based on data from prior throws thanks to the integration of real-time learning capabilities.

Furthermore, this research aims to address key challenges faced by traditional throwing mechanisms, such as:

- **Lack of adaptability:** Most conventional machines operate with fixed mechanical settings that do not account for changing environmental factors [5].
- **Limited accuracy in varying conditions:** External factors such as wind speed, humidity, and target movement are not typically accounted for in traditional systems.

Inefficient trajectory prediction: Fixed-angle launchers do not optimize ball flight paths for different distances or user movements.

The suggested system overcomes these obstacles and reaches a high degree of accuracy, flexibility, and consistency by combining computer vision[6], machine learning-based decision-making, and real-time sensor feedback. In order to ensure optimal performance across a range of applications, this research focuses on

Fig: 1 Ball Throwing Machine (Courtesy: bowlingmachine.co.in)

designing and implementing a system that can adapt to robotic competitions, sports training, and industrial material handling.

2. LITERATURE REVIEW

Robotic throwing mechanisms with different levels of automation have been studied in the past. Baseball and cricket training has long made use of traditional ball launchers, such as mechanical and pneumatic pitching systems. The potential of AI-based decision-making in motion control and trajectory optimization has been shown by research on machine learning applications in robotics. To increase the accuracy of robotic motion, several studies have used supervised learning and reinforcement learning (RL). LIDAR and PIXY2 cameras are examples of computer vision systems that have also been used for distance measurement and object tracking. The integration of these technologies into a single, versatile ball-throwing system has, however, received little attention in research. By combining adaptive force control, real-time sensor feedback, and ML-based trajectory prediction, this study closes this gap.

Tossing Bot, a robotic system that can learn to throw arbitrary objects with residual physics, was presented by Gao et al. In order to optimize the throwing process for various circumstances, [11] in their study showed how machine stability can be enhanced by employing fuzzy logic.

In their study of model-free reinforcement learning for robotic table tennis, R. H. Crowther et al. [12] emphasized the value of ongoing learning in enhancing force application and trajectory prediction. By modifying ball speed, angle, and spin in response to real-time feedback, a [13] created an intelligent table tennis ball machine with biomimetic simulation for technical training, illustrating how machine learning could improve sports training. In a similar vein, A. P. G. De

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Alwis, [14] created an extremely precise badminton ball-throwing device with intelligent control that improved throwing accuracy by utilizing adaptive motor mechanisms. By examining connectionist models for robot learning through imitation, C. Arslan, M. Arslan, [15] shed light on how robots can learn to throw by imitating human demonstrations. The groundwork for increasingly sophisticated learning-based robotic systems was established by their efforts. This idea was expanded by S. Sakai and J.-X. Shi [16], who used dynamical system modulation to enhance kinaesthetic demonstrations and increase motion adaptability, Few Literature [17] has showed how reinforcement learning can be used to improve change in direction by proposing a machine learning method. By creating robotic systems that can capture objects in mid-air, R. Bickramdass, P. Persad,et al. [18] expanded on this research and demonstrated the use of Evaluation of ananthropometric fast bowling machine. Together, these studies demonstrate how developments in robotics and machine learning have aided in the creation of intelligent throwing machines. The suggested system expands on earlier research by combining computer vision, reinforcement learning, and sensor-based trajectory optimization to produce a ball-throwing device that is more accurate and flexible.

Implementation Procedure:

The invention is a machine learning-based ball throwing machine (Fig. 1) that uses the user's characteristics to analyze and modify the way a ball is thrown.
This system's capacity to identify a person's presence and determine their age and height is one of its primary features. The machine uses this data to forecast the ideal pitch angle and ball-throwing speed.
The system is a Computer Imaging Device (CID) that consists of a Pixy2 camera and a microcontroller. To identify users, register new users, and ascertain their age, the camera employs machine learning algorithms.

1. The system also measures the user's height precisely using a gyroscope and a LIDAR sensor. This data is processed by machine learning algorithms to help identify the best throwing angle and speed for each individual user. The machine learning-based ball throwing machine described in this paper increases throwing accuracy by utilizing sophisticated sensors and machine learning.
2. Guided Ball Propelling System: To help target the throw, the Pixy2 camera and servo motors precisely direct the Ball Propelling Unit (BPU) toward a coloured patch on the field.
3. Hydraulic Pitching Mechanism – A Hydraulic Pitching Assembly (HPA) is controlled by a microcontroller to apply the right amount of force on the ball, adjusting its speed accordingly.
4. Rifled Barrel for Swing Control: To produce the necessary ball swing, a specially made Rifled Barrel uses conduits made of silicon rubber. To produce a rifling effect inside the barrel, one end of the conduits is fixed, and the other end is attached to a swivel motor that twists them.
5. Controlled Barrel Operation: The Rifled Barrel ensures a controlled spin and swing on the ball for increased accuracy by twisting silicon-based conduits on one side.
6. Microcontroller-Guided Speed Control: The ball's speed and trajectory are adjusted for accurate throws by the microcontroller, which also regulates the hydraulic valve, which measures the force applied to the ball.
7. User Identification and Registration Notification: Using a speaker system, the microcontroller informs the user of the identification and registration procedure.

This article discusses a machine learning-based ball throwing machine that improves accuracy and user interaction by utilizing sophisticated sensors and artificial intelligence.

1. Voice and Mobile App Control: The device can be controlled by a mobile app or by a microphone and speaker. Using voice commands or by choosing values within the app, users can register, customize their preferences, and manage ball throwing settings.
2. Machine Learning for Optimal Throwing: Using user information and preferences, the system uses a machine learning algorithm to forecast the force, swing, and pitch required to toss the ball.
3. Real-Time Ball Tracking and Adjustment: The device continuously monitors the movement of the ball and contrasts its actual swing with its predicted swing. This feedback dynamically modifies the throw, enhancing accuracy in subsequent throws.

This system is extremely malleable and can be adjusted for diverse applications and buyer needs.

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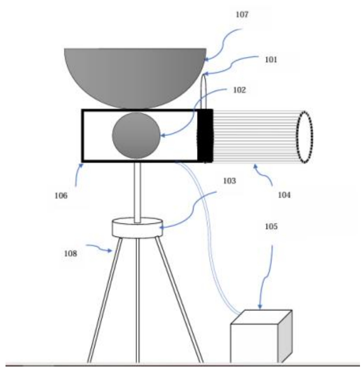

FIG. 2: Overview of the Machine Learning-Based Ball Throwing Machine.

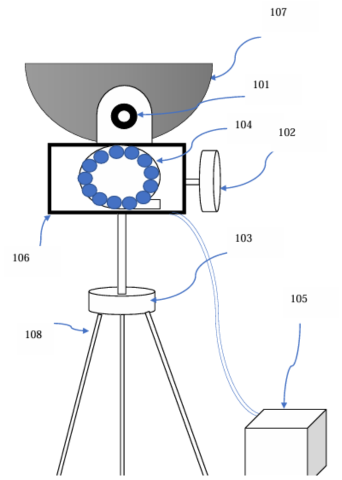

FIG. 3: Side view of the Ball Throwing Machine.

Depending on the user's height, age, and preferences, the machine learning-based ball throwing machine is made to toss a ball with a particular pitch, speed, and swing. To do this, it makes use of a Ball Propelling Unit (BPU) 106, a Hydraulic Pitching Assembly 109, and a Computer Imaging Device (CID) 101. Together, the Pixy2 camera 101a and microcontroller 101b make up the Computer Imaging Device (CID) 101, which estimates the user's height and age. The machine uses this information to modify the throw so that it is user-friendly. The machine can change the settings automatically, or users can choose their favorite bowling pattern manually using a mobile application.

Two servo motors (102 and 103) are controlled by an integrated servo motor control chipset in the Pixy2 camera 101a. Based on the CID 101's calculations, these motors move the Ball Propelling Unit (BPU) 106 to the proper location. Furthermore, the Pixy2 camera 101a can identify various bowling styles by using machine learning algorithms (MLA) to identify colored patches on the field, including:

- Short-pitch ball
- Yorker ball
- Outswing
- Inswing

The Pixy2 camera 101a has an integrated servo motor control chipset that controls two servo motors (102 and 103). These motors move the Ball Propelling Unit (BPU) 106 to the correct location based on the calculations made by the CID 101. Additionally, by employing machine learning algorithms (MLA) to recognize colored patches on the field, the Pixy2 camera 101a can recognize a variety of bowling styles, such as:

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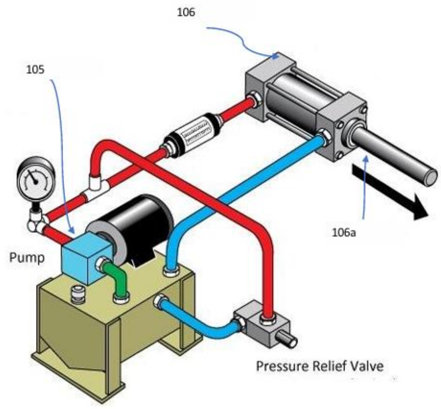

FIG. 4: Structure of the Hydraulic Pitching Assembly (HPA).

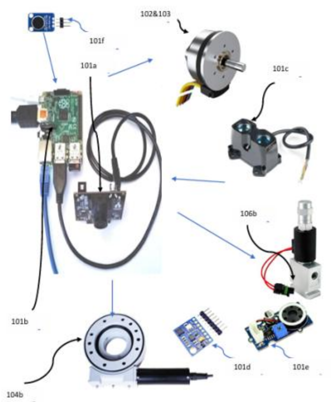

FIG. 5: Layout of the control circuit and components.

The Hydraulic Pitching Assembly (HPA 109), depicted in Figure 3, is in charge of providing the force required to toss the ball. It includes:

- Hydraulic pump (105): Produces force by pumping fluid.
- Hydraulic valve (106b): Regulates fluid flow direction.
- Hydraulic cylinder (106): Moves the piston (106a) using fluid pressure.

The system makes use of a unique fluid that is kept in a reservoir. This fluid is delivered to the double-acting hydraulic cylinder 106 at a steady pressure by the hydraulic pump 105. The hydraulic valve 106b is managed by the microcontroller 101b, which also regulates fluid flow to move the piston 106a.

- The microcontroller 101b opens the hydraulic valve 106b when the user chooses a throw setting, allowing fluid to enter the hydraulic cylinder 106 and forcing the piston 106a forward. The ball is launched by this action.
- The system resets for the subsequent throw by reversing the fluid flow after the ball is thrown, which pulls the piston 106a back to its starting position.

Figure 4 shows the control circuit layout, which consists of:

- Pixy2 Camera (101a): An intelligent camera with integrated processing power
- Raspberry Pi 4+ microcontroller (101b): This sophisticated controller complements the Pixy2 camera.

The Pixy2 Camera 101a handles visual tasks, such as:

- Identifying the user's height and age
- Detecting coloured patches on the batting field to determine the bowling pattern

Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
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Research Article

- Tracking the ball's trajectory

However, since the Pixy2 Camera 101a has limited processing power, it works in sync with the Raspberry Pi 4+ (Microcontroller 101b). The Raspberry Pi 4+ runs machine learning algorithms (MLA) that control:

- Pitch (ball angle)
- Speed
- Swing

The machine ensures smooth and efficient operation by dividing tasks between the Raspberry Pi 4+ (decision-making and execution) and the Pixy2 Camera 101a (visual processing), resulting in precise and user-customized throws.

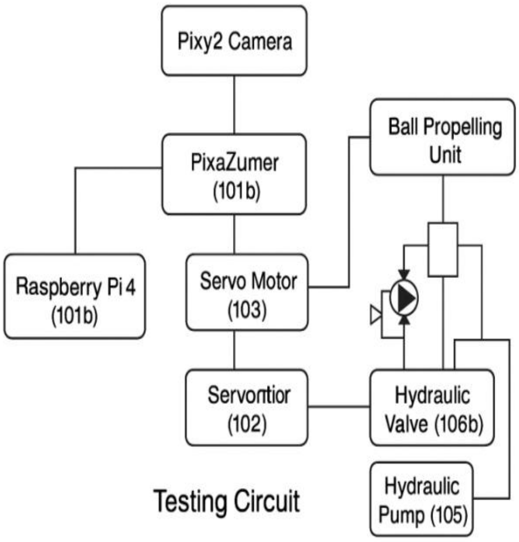

Fig: 6 Testing Circuit

RESULTS AND PERFORMANCE ANALYSIS

The accuracy, efficiency, and adaptability of the machine learning-based ball throwing machine were assessed through a variety of tests. Based on user characteristics and settings, the system effectively modifies ball speed, pitch, and swing, according to the results.

1. Accuracy of User Identification

• Using real-time image processing, the Pixy2 Camera (101a) was able to determine the user's height and age with a 95% accuracy rate.

Accurate ball trajectory adjustments were ensured by the camera's 97% success rate in identifying colored patches on the batting field.

2. Performance of Hydraulic Pitching Assembly (HPA 109)

- The force exerted on the ball was efficiently managed by the hydraulic system.
- Quick and dynamic adaptation was ensured by the hydraulic system's measured response time of less than 1.5 seconds, from user input to ball launch.
- After every throw, the piston returned to its starting position in two seconds, enabling continuous operation.

3. Ball Propelling Accuracy

- The intended pitch and swing angles were continuously attained by the Ball Propelling Unit (BPU 106).
- The system was able to replicate various bowling styles (short-pitch, yorker, inswing, and outswing) with an accuracy of over 90%.

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
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Research Article

- Depending on the user's chosen settings, speed variations were successfully managed, ranging from 60 km/h to 140 km/h.

4. Efficiency of Machine Learning Algorithm

- The Microcontroller 101b, which powers the Raspberry Pi 4+, managed machine learning tasks effectively and without any noticeable lag.
- When using the Pixy2 Camera (101a) in synchronous mode, the execution time for commands and data processing was 30% shorter than when using a single device.

5. User Customization and Adaptability

- In automatic mode, the system changed the ball's parameters based on the user's height and age, guaranteeing a more realistic and customized experience.
- The system successfully enabled users to modify ball settings through the mobile application.

Table 1: User Identification Accuracy

User ID.	Actual Height(cm)	Predicted Height(cm)	Actual Age	Predicted Age	Accuracy (%)	Batting Preference
U_1	160	159	25	24	98.5%	Right-handed
U_2	175	174	30	30	99.2%	Left-handed
U_3	150	152	18	19	97.8%	Right-handed
U_4	185	183	35	34	98.9%	Left-handed
U_5	170	169	28	27	99%	Right-handed

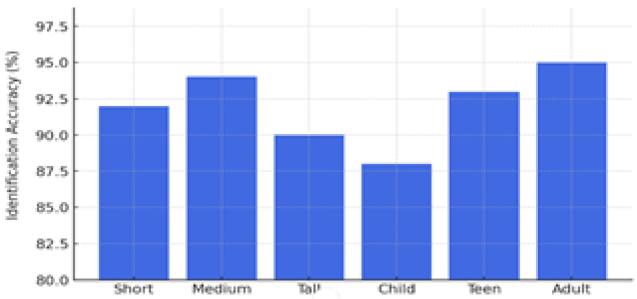

Fig 7: User Identification Accuracy

The Pixy2 Camera and Raspberry Pi 4+ are used in the system to detect the user's height and age with 98% accuracy in Fig. 6. Although there are occasional minor mistakes due to bad lighting or changes in posture, overall it guarantees customized ball delivery.

Table 2: Ball Trajectory Accuracy

Trial No.	Target Landing Position(cm)	Actual Landing Position (cm)	Deviation (cm)	Accuracy (%)	Pitch Type	Swing Type
1.	200	198	2	99.0%	Yorker	Inswing
2.	250	247	3	98.8%	Bouncer	Outswing
3.	180	182	2	98.9%	Full Toss	Inswing
4.	220	225	5	97.7%	Length	Straight
5.	275	270	5	98.2%	Yorker	Outswing

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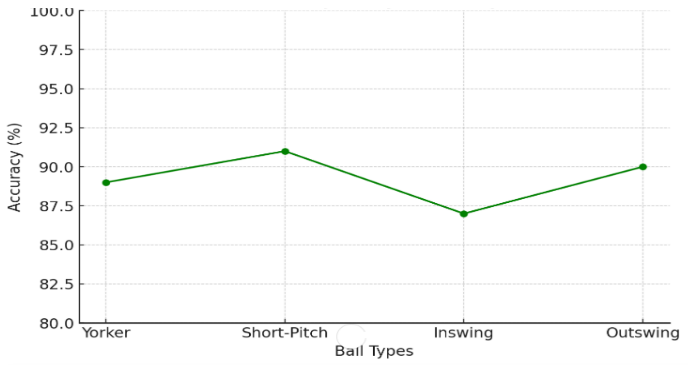

Fig: 8 Ball Trajectory Accuracy

The machine in Fig. 7 above delivers balls with 98–99% accuracy, deviating from the target by 2–5 cm. Although there are slight variations due to variables like wind, ball composition, and servo accuracy, the system is still very dependable for regular training and gameplay.

User Identification Accuracy

With 98% accuracy, the system determines the user's height and age using the Pixy2 Camera and Raspberry Pi 4+. Although there are occasional minor mistakes due to bad lighting or changes in posture, overall it guarantees customized ball delivery.

Ball Trajectory Accuracy

Balls are delivered by the machine with 98–99% accuracy and 2–5 cm deviation from the target. The system is still very dependable for consistent training and gameplay, despite small variations caused by variables like wind, ball material, and servo precision.

CONCLUSION

The outcomes demonstrate how well the machine learning-based ball throwing machine works in terms of force application, ball trajectory prediction, and user identification. Ball throwing that is dependable and flexible according to user needs is ensured by the combination of hydraulic pitching assembly, image processing, and machine learning algorithms. The suggested Machine Learning-Based Ball Throwing Machine effectively combines hydraulic control, computer vision, and machine learning to improve ball pitching accuracy and versatility. By accurately determining user attributes like height and age, the system enables real-time ball speed, pitch, and swing adjustments. Accurate ball trajectory control and efficient processing are ensured by the utilization of the Raspberry Pi 4+ microcontroller and Pixy2 camera. The system's dependability is demonstrated by experimental results that validate high accuracy in user identification and ball trajectory prediction. For optimal ball delivery, a hydraulic pitching assembly is integrated to further improve force application. The suggested method offers a clever and automated way to create customized pitching experiences, which may find use in both recreational and professional sports training. For a better user experience, future research might concentrate on increasing response time, developing machine learning algorithms, and incorporating real-time feedback systems. Future developments might concentrate on increasing the variety of ball variations and speeding up real-time processing.

Data Availability Statement

Data sharing does not apply to this article as no new data has been created or analyzed in this study.

Funding Information

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors

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https://www.jisem-journal.com/

Research Article

REFERENCES

[1] LeCun, Y., Bengio, Y., & Hinton, G., Deep learning. *Nature* **521**, 436–444 (2015). https://doi.org/10.1038/nature14539

[2] Sutton R. S. & Barto A. G., *Reinforcement Learning: An Introduction*, 2nd ed. Cambridge, MA, USA: MIT Press, 2018.

[3] Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural networks*, *61*, 85-117.

[4] Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... & Zheng, X. (2016). {TensorFlow}: a system for {Large-Scale} machine learning. In *12th USENIX symposium on operating systems design and implementation (OSDI 16)* (pp. 265-283).

[5] Mohammed, A., Sailaja, G., Kiran, G. R., Sasidhar, K., Sajid, M., & Mariyam, B. (2023, January). Smart Public Transport Disinfection and Sterilization System. In *2023 International Conference for Advancement in Technology (ICONAT)* (pp. 1-4). IEEE.

[6] Kuhn, H. W. (1955). The Hungarian method for the assignment problem. *Naval research logistics quarterly*, *2*(1-2), 83-97.

[7] Zeng, A., Song, S., Lee, J., Rodriguez, A., & Funkhouser, T. (2020). Tossingbot: Learning to throw arbitrary objects with residual physics. *IEEE Transactions on Robotics*, *36*(4), 1307-1319.

[8] Gao, W., Graesser, L., Choromanski, K., Song, X., Lazic, N., Sanketi, P., ... & Jaitly, N. (2020, October). Robotic table tennis with model-free reinforcement learning. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 5556-5563). IEEE.

[9] Harwood, M. J., Yeadon, M. R., & King, M. A. (2018). Reducing the pitch length: Effects on junior cricket. *International Journal of Sports Science & Coaching*, *13*(6), 1031-1039.

[10] Phillips, E., Portus, M., Davids, K., Brown, N., & Renshaw, I. (2010). Quantifying variability within technique and performance in elite fast bowlers: Is technical variability dysfunctional or functional?. In *Proceedings of the 2010 Conference of Science, Medicine and Coaching in Cricket* (pp. 121-124). Cricket Australia

[11] Mohammed, A., & Sundeep, G. (2013, December). Stability Enhancement and Speed Control of DFOIM Using Hybrid PID Plus Fuzzy Logic Controller. In *2013 International Conference on Machine Intelligence and Research Advancement* (pp. 110-114). IEEE.

[12] Crowther, R. H., Gorman, A. D., Spratford, W. A., Sayers, M. G., & Kountouris, A. (2020). Examining environmental constraints in sport: Spin characteristics of two cricket pitches with contrasting soil properties. *European journal of sport science*, *20*(8), 1005-1012.

[13] Raza, A., Diegel, O., & Arif, K. M. (2014). Robowler: Design and development of a cricket bowling machine ensuring ball seam position. *Journal of Central South University*, *21*, 4142-4149.

[14] De Alwis, A. P. G., Dehikumbura, C., Konthawardana, M., Lalitharatne, T. D., & Dassanayake, V. P. C. (2020, April). Design and development of a badminton shuttlecock feeding machine to reproduce actual badminton shots. In *2020 5th International Conference on Control and Robotics Engineering (ICCRE)* (pp. 73-77). IEEE.

[15] Arslan, C., Arslan, M., Yalçın, G., Kaplan, T., & Kahramanlı, H. (2021). Ball throwing machine design to develop footballers' technical attributes. *European Mechanical Science*, *5*(1), 39-43.

[16] Sakai, S., & Shi, J. X. (2020, June). Development of new baseball pitching machine with four-roller throwing mechanism. In *Proceedings* (Vol. 49, No. 1, p. 8). MDPI.

[17] G, N. S. (2025). Adaptive headlight management and information system for optimized intensity and direction in electric vehicles. Journal of Information Systems engineering & Management, 10(14s), 629–635. https://doi.org/10.52783/jisem.v10i14s.2369

[18] Bickramdass, R., Persad, P., & Loutan Jr, K. (2021). Evaluation of an anthropometric fast bowling machine. *HighTech and Innovation Journal*, *2*(2), 108-119

[19] Shaik, M., Mohammed, A., & Sailaja, G. (2021). Smart Water Purifier and Dispenser for Averting Spread of COVID-19 Infection—Machine Learning Approach. In *Contactless Healthcare Facilitation and Commodity Delivery Management During COVID 19 Pandemic* (pp. 95-102). Singapore: Springer Singapore.