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Smart Umpiring for LBW Detection System

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Abstract: In cricket, Leg Before Wicket (LBW) decisions have long been a subject of controversy and debate, often relying on the subjective judgment of on-field umpires. With the advent of advanced technologies, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools to enhance decision-making accuracy in sports. The proposed system presents AI-based LBW detection systems, exploring the integration of computer vision, ball tracking procedures, pose estimation, and predictive models to improve real-time predictions and reduce human. The combination of Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM) classifiers can achieve approximately 80–90% accuracy in classification tasks such as ball detection and LBW decision-making using side-on video footage.

Keywords: Leg Before Wicket (LBW), Artificial Intelligence (AI), Machine Learning (ML), Umpire, HOG.

I. INTRODUCTION

Cricket is the second most followed sports in the world which was invented by English people and spread between the countries. Cricket is a game where accurate decision-making is crucial, especially in cases like Leg Before Wicket (LBW), which require the umpire to make fast and precise judgments based on the ball's path, bounce, angle, and point of impact. The project aims to automate this complex process using artificial intelligence, computer vision, and predictive modeling. The system begins by capturing live video or sensor data from high-speed cameras placed around the cricket field. This input is broken down into frames for analysis, and object detection algorithms are applied to identify and track the ball, batsman, stumps, and other relevant elements. Once the objects are detected, the trajectory of the ball is extracted, which includes calculating its 2D or 3D path, bounce point, and the moment of impact with the batsman. To predict where the ball would have gone after impact, the system uses either a physics-based model or a machine learning approach such as Long Short-Term Memory (LSTM) networks, which are well-suited for time-series prediction. Based on the predicted trajectory and established cricket rules, the system makes a decision on whether the batsman is out or not out. This decision is then visually presented through an interface designed for umpires and review officials, providing clear and reliable feedback that improves the accuracy and fairness of LBW decisions. By minimizing human error and delivering real-time insights, this AI-powered system supports smarter officiating and enhances the overall integrity of the game. Cricket is a sport that relies heavily on the accuracy and fairness of umpiring decisions. One of the most debated and complex decisions in the game is Leg before Wicket (LBW), where the umpire must judge whether the ball would have hit the stumps had it not struck the batsman’s leg. This decision requires rapid interpretation of the ball’s speed, angle, spin, bounce, and point of impact—often under high pressure and in real time. This addresses this challenge by developing an intelligent system that replicates and enhances the LBW decision-making process using artificial intelligence, image processing, and trajectory modeling. The goal is to assist umpires with accurate, real-time decisions, minimize human error, and bring transparency and consistency to the game. This system captures video or sensor-based input data from live matches and processes it through a pipeline of advanced modules. These modules include frame extraction, object detection (to identify the ball, batsman, and stumps), and trajectory extraction to trace the 2D/3D path of the ball, including bounce and impact points. Using either a machine learning model such as LSTM or a physics-based model, the system then predicts the ball's future trajectory. Based on this prediction and standard cricket rules, it outputs a decision: Out or Not Out.

II. LITERATURE SURVEY

Krishnan P et al [1] discusses a wearable Decision Review System (DRS) for cricket to improve umpire accuracy in smaller tournaments, where advanced technologies like DRS and snickometer are unavailable. The proposed solution is a smart glass worn by the umpire, equipped with an inbuilt camera and image processing system to record and replay every ball. Controlled via a handheld joystick, this device provides real-time trajectory analysis and statistical data, aiding umpires in making faster and more accurate decisions. The implementation of a wearable DRS system in cricket enhances accuracy, reduces costs, and speeds up decision-making. D. Hemanathan et al [2] the paper introduces an AI-based virtual umpiring system designed to improve decision accuracy and fairness in cricket. It

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leverages computer vision and machine learning to analyze live video feeds, assisting umpires with real-time decision-making. The system tracks ball trajectory and player movements, continuously improving through machine learning. Key features include instant replays and transparency in decisions, highlighting the potential of AI in sports officiating. Virtual umpiring systems have enhanced accuracy, fairness, and efficiency in cricket. Satvik Vats et al [3] presents a model that integrates Convolutional Neural Networks (CNN) and Random Forest (RF) for recognizing cricket umpire gestures. The model's accuracy ranges from 78.10% to 90.83%, demonstrating its reliability. The results show Class 3 performing the best with 85.76% accuracy, 94.87% recall, and a 90.09% F1-score. The overall performance metrics, including macro, micro, and weighted averages, confirm the model's flexibility in recognizing umpire gestures under varying conditions. The results indicate 85.06% overall accuracy, proving its reliability in cricket officiating. Class 3 performed the best, while Class 4 had room for improvement. Rebecca Pattichis et al [4] the paper explores mathematical methods to understand neural networks in image analysis using Linear Algebra. It introduces techniques to model neural network layers as maps between signal spaces. The study visualizes weight spaces, convolutional layer kernels, and residual vector spaces to analyze information loss. It also examines invertible networks using vector spaces to compute input images for specific outputs, applying the approach to ResNet18 and other models. Future research may investigate whether invertible networks can match the performance of non-invertible models, as they allow back-projection of output spaces to input images. Gururaj, B. N et al [5] The study presents a virtual reality (VR) cricket simulator aimed at improving batting skills through an immersive and realistic training environment. Built using Unity3D, the system reduces response delays and provides real-time feedback, enhancing user engagement. The simulator incorporates advanced ball speed measurement and collision detection algorithms, creating realistic bat-ball interactions. Experimental results show improved batting accuracy, with 61% success in back foot shots and 76% in front-foot shots, averaging 68.5% overall accuracy. Ramachandra, A. C et al [6] presents an automated system to enhance the accuracy of umpiring decisions in cricket by detecting illegal bowling deliveries, including no-balls, wide balls, and bounce balls. Given the increasing reliance on technology in modern cricket, the study aims to minimize human errors that often impact match outcomes. Since no standard dataset exists for bowler error detection, a custom dataset was created consisting of 64 images, including: 25 no- ball images (captured from a side view), 24 bounce ball images (captured from multiple angles), 15 wide ball images (captured from a front view). Ramya, P et al [7] the paper presents an AI-driven solution to improve decision-making in cricket. The study aims to enhance the accuracy and efficiency of third umpire decisions, particularly for Leg Before Wicket (LBW) calls, and to generate automated pitch reports. This data helps teams decide on their strategy and playing XI. The system also integrates a voice-recognition AI (Alan-AI) to assist umpires in recalling cricket laws, making the decision process more transparent. A user-friendly GUI is developed using Tkinter, while OpenCV and imutils facilitate video processing .Fernandes, J. B. et al [8] explores the use of deep learning techniques to automatically detect and classify cricket shots from images. Given the increasing popularity of cricket and the vast amount of video footage generated, automated shot detection can significantly aid in performance analysis, coaching, and match analytics. The study proposes a 2D Convolutional Neural Network (CNN) model with multiple layers, including convolution, pooling, flattening, and fully connected layers, to extract features from images and classify different batting shots. The model is trained and tested on a separate test set, achieving an overall accuracy of 91.5% in detecting different types of shots.

Bhat, R.S et al [9] proposes an automated approach to generate cricket match highlights using deep learning techniques. Given the long duration of cricket matches, manually creating highlights is time-consuming and requires expert editing. The proposed system processes input match videos to generate three types of summaries: a highlight video, a textual summary, and an audio summary. The system was evaluated against manually created highlights and was found to successfully capture 80-90% of key events, achieving a BLEU-4 score of 0.748953 for textual summarization .[10] introduces an automated system that enhances umpiring decisions by detecting illegal bowling actions such as front-foot no-balls and arm overextensions in real time. Traditional umpiring methods rely on human judgment and slow-motion video reviews, which can be time-consuming and prone to error. When a front-foot no-ball is detected, the system instantly alerts the TV umpire and generates a 3D visualization for broadcasting. The system was successfully tested during the *ICC T20 World Cup 2022* and other major tournaments, achieving 100% accuracy in detecting no- balls without false positives. [11] Presents a computer vision based approach to automatically identify and classify cricket poses using keypoint detection techniques. By leveraging deep learning models such as Open Pose or Media Pipe, the study extracts key body joints from images or video frames to recognize

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different cricket actions like batting, bowling, wicket keeping, and fielding. The extracted key points are then processed using machine learning classifiers to accurately categorize player movements. This research has significant applications in sports analytics, coaching, and performance evaluation, enabling automated assessment without manual intervention. Sakib, S et al [12] explores an AI-driven approach to automatically detect cricket events by analyzing umpire signals in videos. The authors employ Convolutional Neural Networks (CNNs) to process video frames and classify different umpire gestures, such as signaling for a boundary, six, out, wide ball, or no-ball. By using deep learning techniques, the system extracts meaningful features from video sequences to improve the accuracy of event recognition. This research has significant applications in sports analytics, automated match summarization, and real-time decision-making. The study also addresses challenges like occlusions, varying lighting conditions, and differences in umpire signaling styles, ensuring robust detection across diverse scenarios.

Sikandar, S et.al [13] presents a deep learning-based approach to automatically generate summaries of cricket matches. The authors propose a novel Convolutional Neural Network (CNN) model that analyzes video frames to detect key moments such as wickets, boundaries, and crucial player actions. By extracting important frames and filtering out less relevant content, the system creates a concise and informative highlight reel. This research has applications in automated sports summarization, real-time match analysis, and personalized content generation. Chitra, R. et.al [14] proposed an Internet of Things (IoT) based system for accurately detecting runouts in cricket. The authors integrate IoT sensors, computer vision, and real-time data processing to automate the decision-making process. The system likely uses high speed cameras, motion sensors, and microcontrollers to track the ball, bat, and player movements near the crease. This approach enhances accuracy, reduces human errors, and speeds up runout decisions, benefiting umpires, players, and broadcasters. Nasir, T. et.al [15] presents a deep learning-based method to automatically generate highlights from cricket matches. The authors use Convolutional Neural Networks (CNNs) and other deep learning models to analyze video frames and identify key events such as wickets, boundaries, and celebrations. By filtering out less significant moments, the system creates concise and engaging summaries for viewers. This approach enhances sports analytics, content creation, and fan engagement by providing quick access to important match highlights. Kapil Gupta et.al [16] introduces a data-driven approach to evaluating batting performance in women's cricket. The study employs Principal Component Analysis (PCA) and Gini scores to assess and rank players based on multiple performance metrics such as runs scored, strike rate, consistency, and match impact. PCA is used to reduce dimensionality and identify key factors influencing performance, while Gini scores help measure inequality in a player's scoring distribution. The research also highlights the growing importance of data analytics in women’s cricket, contributing to fairer and more accurate player evaluations. Miftaul Mannan, et.al [17] presents a deep learning-based approach to automatically recognize various cricketing actions from videos. The authors employ Convolutional Neural Networks (CNNs) and other deep learning techniques to detect and classify activities such as batting, bowling, fielding, and umpire signals. The model processes video frames to extract meaningful features, enabling accurate identification of different cricket events. This research has applications in sports analytics, automated match highlights generation, and player performance evaluation. Devanandan, M., et.al [18] presents a machine learning-based approach to categorize different cricket shots from images. The authors use Random Forest, a robust classification algorithm, to analyze key visual features and distinguish between various batting strokes such as drives, pulls, cuts, and sweeps. The study likely involves feature extraction techniques to identify bat angles, player posture, and ball trajectory for accurate classification. This research has applications in sports analytics, coaching assistance, and automated performance evaluation. P. Nirmala Devi et.al [19] presents an AI-based system for automating runout decisions in cricket using image processing techniques. The study focuses on analyzing video frames to detect key elements such as the position of the bat, crease line, and bails at the moment of a possible runout. By applying edge detection, object tracking, and motion analysis algorithms, the system determines whether the batsman is inside the crease before the stumps are broken. This approach enhances decision accuracy, reduces human errors, and speeds up the third umpire review process. Kunpeng Li et.al [20] presents a control strategy for accurately tracking the trajectory of a ball on a plate. The study proposes a robust output regulation method to handle system uncertainties and external disturbances while ensuring precise control of the ball’s movement. Using advanced control algorithms, the system maintains stability and improves tracking performance by adjusting the plate’s tilt dynamically.

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III. METHODOLODY

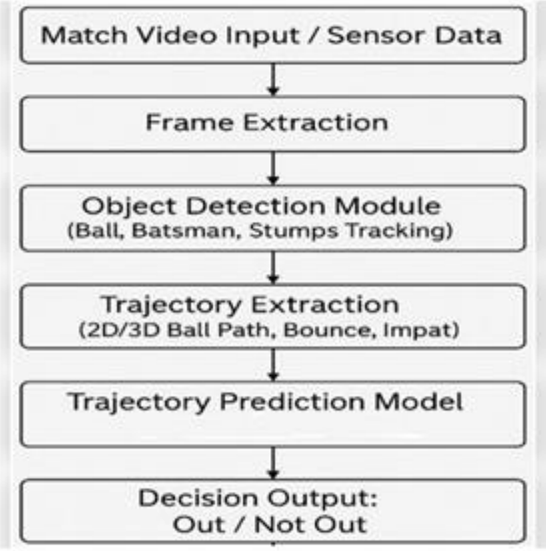

Fig 1: Block Diagram of Proposed System

The AI-based LBW decision-making system begins with collecting data from high-speed cameras and tracking sensors placed around the cricket ground. These inputs capture detailed visual and motion data of the ball and players in real time. The recorded video is then split into individual frames through frame extraction, enabling the system to analyze each moment of play accurately. In the next step, an object detection module identifies and tracks key elements in each frame, such as the ball, batsman, and stumps. This is achieved using computer vision and deep learning techniques like YOLO or OpenCV. Once the objects are detected, the trajectory extraction module reconstructs the ball's 2D or 3D path, identifying critical points such as the bounce, point of impact, and pre-impact direction. To determine the likely outcome, a trajectory prediction model is used. This can be an LSTM-based deep learning model, which learns from sequential ball positions, or a physics-based model that uses motion equations to simulate where the ball would have gone after hitting the batsman. Based on this analysis and the rules of cricket, the system decides whether the batsman is Out or Not Out. Finally, a visual display interface presents the decision along with supporting visuals—such as replays, bounce point, impact location, and predicted trajectory—to umpires, players, and viewers. This enhances the transparency and accuracy of umpiring decisions using AI technology.

3.1 Algorithms

1. Ball Tracking Algorithm

1. Start
2. Receive preprocessed video frames
3. Detect cricket ball using object detection
4. Track ball position frame by frame
5. Store speed, angle, and position data
6. Stop

2. Trajectory Prediction Algorithm

1. Start
2. Input tracked ball data
3. Apply physics-based or ML prediction model
4. Simulate path after impact
5. Predict if ball hits stumps
6. Output trajectory result
7. Stop

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3. LBW Decision Logic Algorithm

1. Start
2. Check if ball pitched in line
3. Check if impact is in line
4. Check if predicted path hits stumps
5. If all true → Decision = OUT
6. Else → Decision = NOT OUT
7. Stop

3.2 Hardware Setup:

High-speed cameras play a crucial role in capturing the rapid movement of the ball and key contact points with high clarity. Strategically positioned around the field, these cameras enable accurate 3D tracking of the ball's motion and provide continuous video frames to the AI system in real-time. To process this data effectively, a GPU-enabled processing unit is employed. This unit runs machine learning models responsible for predicting the ball's trajectory and point of impact, handling large volumes of video data swiftly to ensure fast and accurate decision-making during the match. Infrared or ball tracking sensors complement the visual data by offering precise measurements of the ball's position and velocity, especially in scenarios where video quality might be compromised due to lighting or weather conditions. The third umpire views the outcome of this analysis on a dedicated display screen, which presents replays, impact points, and AI-generated decisions. This interface not only aids the umpire in making quick and reliable judgments but can also be connected to stadium displays for public viewing. Additionally, a data storage unit is incorporated into the system to archive both video footage and AI-generated predictions. This storage allows for post-match reviews and audits, helping validate decisions and also offering valuable data for further training and enhancement of AI models over time.

3.3 System Architecture:

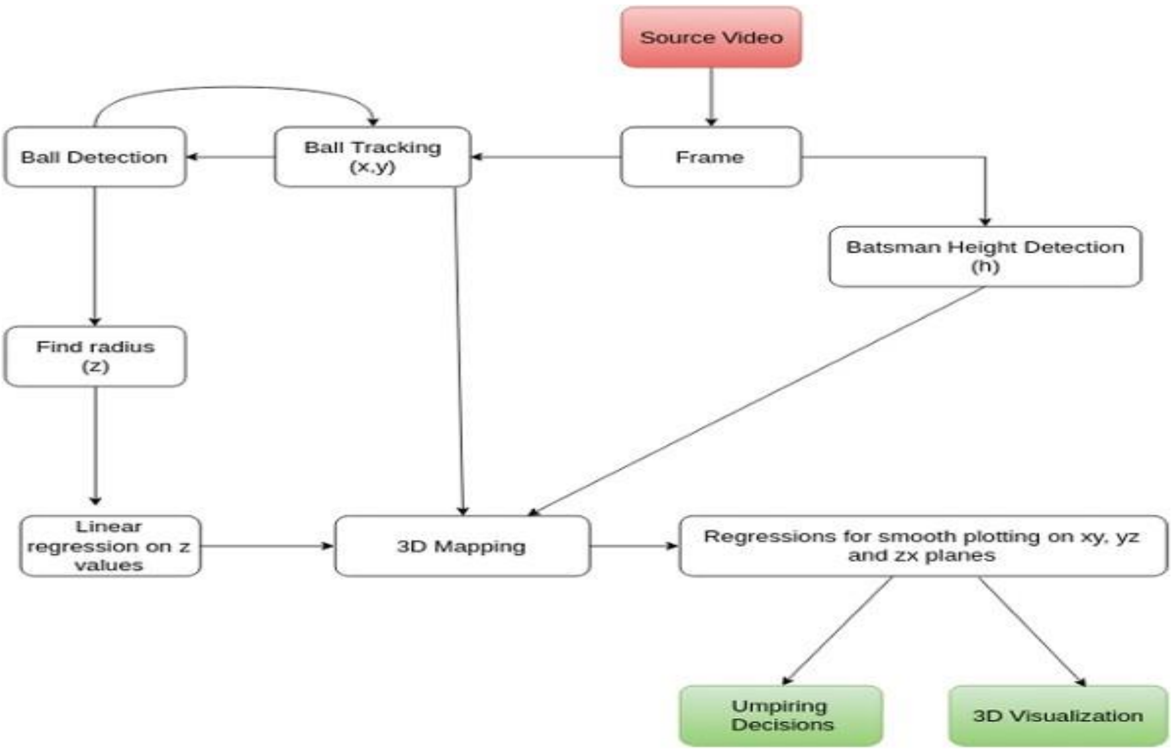

Figure 2: System Architecture

1. **Ball Detection**: In each frame, the system detects the cricket ball using color filtering, contour detection, or shape recognition to isolate the ball from the scene.

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2. **Ball Tracking:** The system tracks the ball's position (x, y coordinates) across frames, building its 2D path from the bowler to the batsman.
3. **Ball Radius and Depth Calculation:** The ball's radius is calculated in each frame, helping estimate its depth (z-value), which is smoothed using linear regression for more accurate distance measurements.
4. **Batsman Height Extraction:** The system extracts the batsman's height from frames by identifying the top and bottom coordinates, essential for LBW decisions.
5. **3D Mapping:** The ball's coordinates (x, y, and z) and batsman's height are combined to generate a 3D representation of the ball's path and interaction with the batsman.
6. **Regression Analysis:** Regression analysis is applied on all three spatial planes (xy, yz, zx) to smooth the ball's trajectory and predict its uninterrupted path.
7. **Umpiring Decision**: Based on predefined rules, the system outputs a decision on whether the ball would have hit the stumps, supporting or replacing human umpiring.
8. **3D Visualization:** The system produces a 3D visualization of the ball’s trajectory, providing transparency and supporting decisions, similar to professional technologies like Hawk-Eye.

IV. RESULTS AND ANALYSIS

Figure 3: Bowler and batsman Action

The image shown represents a frame of raw video data used for training or testing an AI system designed to detect Leg Before Wicket (LBW) decisions in cricket. The scenario captures a bowler delivering the ball to a batsman with fielders and the umpire in view, offering a real-time match situation from a strategic camera angle.

Figure 4: Bowler Action

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Figure 5: Batsman Action

These images capture a key frame for AI-based LBW detection, where computer vision tracks the ball's path and point of impact. Machine learning algorithms then predict the trajectory to assist the third umpire in making an accurate Out or Not Out decision. This also shows a crucial LBW moment where the ball strikes the batsman's pad in front of the stumps. Using AI-based third umpire systems, such frames help analyze ball impact and predicted trajectory to accurately determine an Out or Not Out decision.

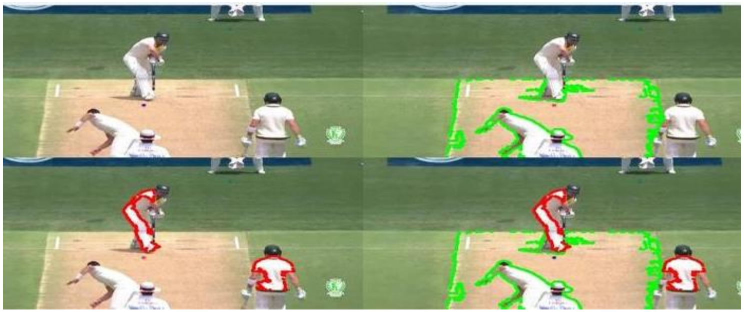

Figure 6: Working View of the proposed system

Final Display of the Project" presents a visual summary of the third umpire LBW detection system using AI. It showcases four key frames extracted from a cricket video where the AI algorithm has been applied to detect and highlight the players and the action zones on the pitch.

CONCLUSION

This proposed work aimed to assist cricket umpires in LBW decision-making using a single-camera system powered by computer vision and machine learning. Algorithms for ball detection and tracking were developed using HOG and SVM, achieving promising accuracy. The system automates key tasks, reducing human error and enhancing real-time decision-making. Results demonstrate the potential of AI in improving umpiring accuracy. This study also lays the groundwork for future research in AI-based sports analytics, with scope for further enhancements and broader applications

REFERENCES

[1] Krishnan, P. S., M., B., Amudhan, T., Dharshini, P. N., & Kiruphashni, B. (2024). "On Field Third Eye." 2024 International Conference on Communication, Computing and Internet of Things (IC3IoT), 22-23 February 2024, Chennai, India. IEEE. https://doi.org/10.1109/IC3IoT60841.2024.10550304.

[2] D. Hemanathan, Vanitha, R., Vishwa, R., & Shalini, S. (2024). "Virtual Umpiring and Ball Tracking System by Image Processing using ResNet-18." Grenze International Journal of Engineering and Technology (GIJET). Grenze Scientific Society.

[3] Satvik Vats , Chauhan, R. K., & Mehta, S. (2024). "Innovative Approaches for Action Detection: Leveraging CNN- RF in Cricket Umpire for Gesture Recognition." 15th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 18-20 July 2024, Kharagpur, India. IEEE.

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https://doi.org/10.1109/ICCCNT61001.2024.10725292.

[4] Pattichis, R., & Pattichis, M. S. (2024). "Understanding Neural Network Systems for Image Analysis Using Vector Spaces." 2024 IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI), 17-19 March 2024, Santa Fe, USA. IEEE. https://doi.org/10.1109/SSIAI59505.2024.10508639.

[5] Gururaj, B. N., & Sooda, K. (2024). "Design of a Comprehensive Virtual Reality Cricket Simulator for Immersive Skill Training." 2024 8th International Conference on Computational System and Information Technology for Sustainable Solutions (CSITSS), Bangalore, India. IEEE. https://doi.org/10.1109/CSITSS64042.2024.10816833.

[6] Ramachandra, A. C., Akanksha, K., Harshitha, G., & Dixith, K. S. (2023). "Detection of Bowler Errors using Deep Learning." International Conference on Applied Intelligence and Sustainable Computing (ICAISC), Bengaluru, India. IEEE https://doi.org/10.1109/ICAISC58445.2023.10200514.

[7] Ramya, P., Gowtham, C. P., Kumar, S. K., Silpica, T. P., & Renugadevi, P. (2023). "A Customisable AI Deck for Pitch Reports and Automated III Umpire Decision Review System (DRS)." 2nd International Conference on Edge Computing and Applications (ICECAA), 26-27 May 2023, Bangalore, India. IEEE. https://doi.org/10.1109/ICECAA58104.2023.10212245.

[8] Fernandes, J. B., Kumar, K. P. (2023). "Cricket Shot Detection using 2D CNN." 7th International Conference on Intelligent Computing and Control Systems (ICICCS), 17-19 May 2023, Madurai, India. IEEE. https://doi.org/10.1109/ICICCS56967.2023.10142272.

[9] Bhat, R. S., Jayanth, O., Prasad, P. P., Vedurumudi, P. K., & Divyaprabha, K. N. (2023). "Cricket Video Summarization Using Deep Learning." 8th IEEE International Conference for Convergence in Technology (I2CT), Pune, India. IEEE. https://doi.org/10.1109/I2CT57861.2023.10126359.

[10] Izadi, M., Goodarzi, E., Farzalizadeh, M., Moghadam, M. M., & Izmailov, A. (2023). "Officiating Cricket Bowling Using An Event-Based Computer Vision System." 2023 IEEE 28th Pacific Rim International Symposium on Dependable Computing (PRDC), 29 Nov - 1 Dec 2023, Singapore. IEEE. https://doi.org/10.1109/PRDC59308.2023.00047.

[11] Mili, R., Das, N. R., Tandon, A., Mokhtar, S., Mukherjee, I., & Paul, G. (2022). "Pose Recognition in Cricket using Keypoints." 2022 IEEE 9th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), 2-4 Dec 2022, Prayagraj, India. IEEE. https://doi.org/10.1109/UPCON56432.2022.9986481.

[12] Sakib, S., Mridha, M. A. H., Hasan, N., Habib, M. T., & Mahbub, M. S. (2022). "Event Detection from Cricket Videos Using Video-Based CNN Classification of Umpire Signals." 2022 4th International Conference on Sustainable Technologies for Industry 4.0 (STI), Dhaka, Bangladesh. IEEE. https://doi.org/10.1109/STI56238.2022.10103241.

[13] Sikandar, S., Mahmum, R., & Akbar, N. (2022). "Cricket Videos Summary Generation Using a Novel Convolutional Neural Network." 2022 Mohammad Ali Jinnah University International Conference on Computing (MAJICC). IEEE. https://doi.org/10.1109/MAJICC56935.2022.9994106.

[14] Chitra, R., Jayapreetha, N., Swetha, S., & Swetha, D. (2022). "Runout Detection in Cricket Using IoT." 2022 International Conference on Communication, Computing and Internet of Things (IC3IoT). IEEE. https://doi.org/10.1109/IC3IOT53935.2022.9767953.

[15] Nasir, T., Iqbal, M. J., & Anwar, M. (2022). "Summarization of Cricket Videos Using Deep Learning Technique." 2022 International Conference on Frontiers of Information Technology (FIT). IEEE. https://doi.org/10.1109/FIT57066.2022.00016.

[16] Kapil Gupta, (2022). "An integrated batting performance analytics model for women's cricket using Principal Component Analysis and Gini scores." Decision Analytics Journal, 4, 100109. Elsevier. https://doi.org/10.1016/j.dajour.2022.100109.

[17] Miftaul Mannan, Shahriar, A., Rahman, M., & Shahriar, S. M. (2021). "Detection of Cricketing Activities Using Deep Learning." TENCON 2021 - 2021 IEEE Region 10 Conference (TENCON), Auckland, New Zealand, 7-10 Dec 2021. IEEE. https://doi.org/10.1109/TENCON54134.2021.9707392.

[18] Devanandan, M., Asokan, N., Rasaratnam, V., Panchendrarajan, R., Anbalagan, M. K., & Tharmaseelan, J. (2021). "Cricket Shot Image Classification Using Random Forest." 2021 3rd International Conference on Advancements in Computing (ICAC), IEEE. https://doi.org/10.1109/ICAC54203.2021.9671109.

[19] P. Nirmala Devi, (2021). "Artificial Intelligent Third Umpire Runout Decision Making Using Image Processing." Conference Series: Materials Science and Engineering, 1055, 012095. https://doi.org/10.1088/1757- 899X/1055/1/012095.

[20] Kunpeng Li., Ping, Z., Huang, Y., & Lu, J.-G. (2021). "A Robust Output Regulation Approach for Trajectory Tracking Control of Ball and Plate System." Proceedings of the 40th Chinese Control Conference, July 26-28, Shanghai.