



Automatic Scoring System For Badminton Matches Using Computer Vision Techniques

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Abstract— An automatic scoring system for badminton matches using computer vision techniques is presented in this paper. TrackNetV3 is used for shuttlecock detection, and a custom model is used to predict the corners of the badminton court, in order to convert the frame into a top-view perspective. By connecting the most frequent coordinates, the trajectory of the shuttlecock is determined. The shuttle drop detection method identifies frames with speeds below a predetermined threshold, indicating that the shuttlecock has fallen. An additional model is utilized to predict player poses during service, which aids in the decision-making process. As part of the scoring process, the system creates polygons in the top-view image to mark the locations of shuttle drop-offs. This proposed system is effective at scoring badminton matches accurately, as demonstrated by experimental results.

Keywords —

Badminton, Automated Scoring, Computer Vision, TrackNetV3, Shuttlecock Detection, Homography Matrix, CNN, Pose Prediction, Deep learning.

1. INTRODUCTION

Since the explosion of deep learning research in recent years, it has been widely used across a wide range of industries, including sports analytics. The abundance of game footage accessible via the internet has facilitated thorough analysis. Within this context, machine learning has emerged as a pivotal tool, driving the development of automated systems aimed at enhancing the efficiency of game analysis.

In this context, our work is dedicated to the tracking of shuttlecocks in badminton and calculating the score automatically, a sport with a global footprint that requires its participants to engage in strategic planning. The unique attributes of a shuttlecock, including its lightweight nature and rapid motion, present particular challenges for tracking. Firstly,

during a smash, a shuttlecock can achieve instantaneous peak velocities reaching 426 km/h, making it the fastest moving object in all racquet sports. This rapid movement often leads to motion blur when captured by standard cameras, causing a ghosting effect on the shuttlecock. Secondly, the wide-angle perspective of court view shots usually reduces the shuttlecock to a minuscule portion of the frame, further complicating the tracking task. Thirdly, a shuttlecock can blend seamlessly into the background components, such as the net and court lines, rendering it nearly invisible if its dynamics are not analyzed through consecutive video frames. Given these challenges, our goal is to develop a more precise shuttlecock tracking system. The suggested system using TrackNetV3 consists of two fundamental modules: trajectory prediction and rectification. Building on the foundation of TrackNetV2, the trajectory prediction module considers a series of video frames to generate corresponding heat maps that indicate the positions of the shuttlecock. We further enrich this model by feeding it an estimated background, which acts as supplemental information to better differentiate the shuttlecock from various visual distractions. The trajectory prediction module also incorporates mixup data augmentation, creating complex scenarios that enhance the network's robustness. Recognizing that a shuttlecock may occasionally be concealed, making its true position undeterminable through visual cues, we rectify the trajectory based on the shuttlecock's motion dynamics. Specifically, we generate repair masks by assessing the predicted trajectory and train the rectification module that considers the predicted trajectory and the mask for rectification. This process considerably enhances the accuracy of tracking and the completeness of the trajectory. Our system was assessed against advanced techniques like YOLOv7 and TrackNetV2. The results of these comparative experiments demonstrate that TrackNetV3 significantly outperforms these baseline methods, yielding accuracies of 97.51%, contrasted with 94.98% for TrackNetV2 and 53.47% for YOLOv7.

Model	Accuracy	Precision	Recall	F1	FPS
YOLOv7	57.82%	78.53%	59.96%	68.00%	34.77
TrackNetV2	94.98%	99.64%	94.56%	97.03%	27.70
TrackNetV3	97.51%	97.79%	99.33%	98.56%	25.11

Figure 1: Model Comparisons [1]

1.1 Architecture of TrackNetV3

TrackNet V3 is a convolutional neural network architecture designed for multi-object tracking in videos. The architecture consists of several layers, each serving a specific purpose in extracting features and making predictions. Here's a typical layer architecture for a multi-object tracking network like TrackNet V3:

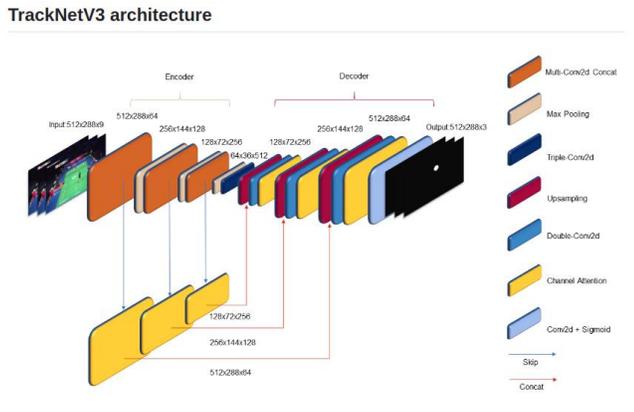


Figure 2: TrackNetV3 Architecture[2]

Key component

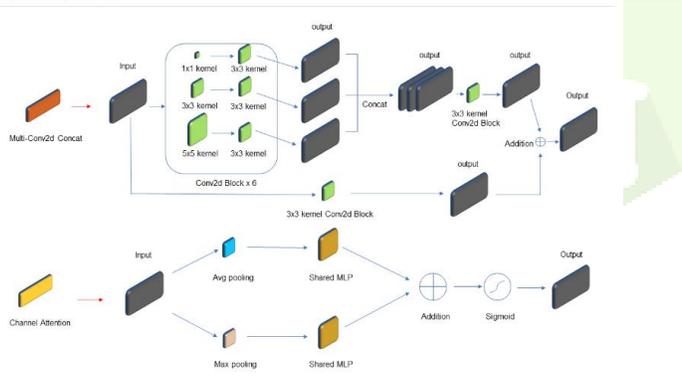
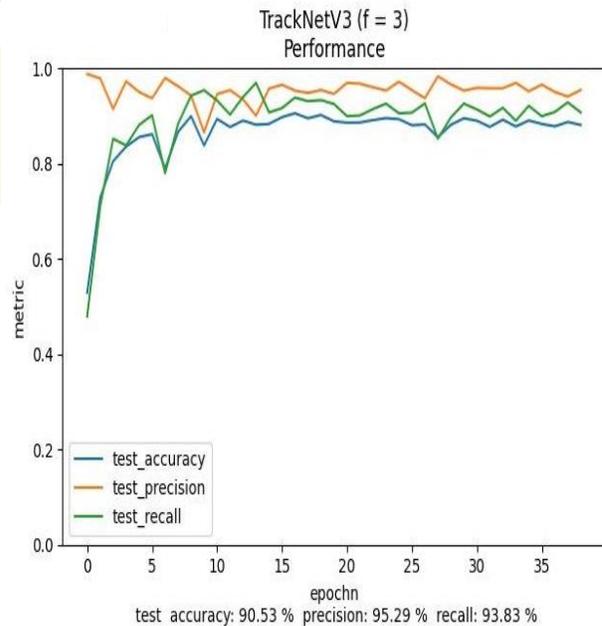
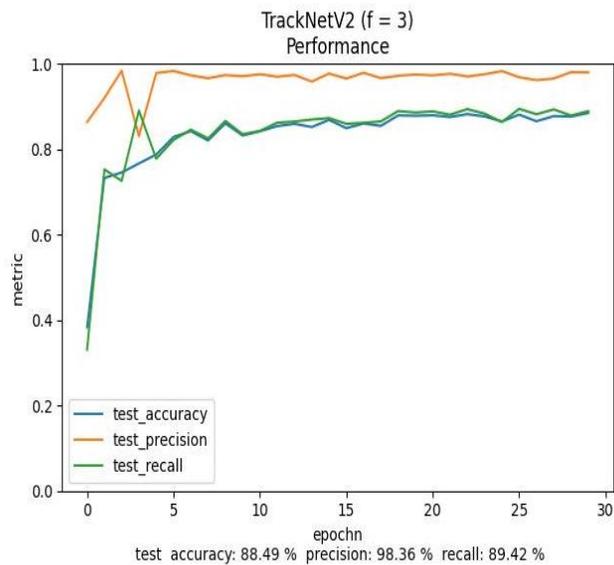


Figure 3: Key Components[2]

1. Input Layer: This layer accepts the input video frames or sequences of frames. The size of the input layer depends on the resolution of the video frames and the number of frames considered for tracking.
2. Convolutional Layers: A series of convolutional layers are used to extract features from the input frames. These layers apply filters to the input data to detect patterns and features relevant to object tracking.
3. Optional use of Recurrent Layers: Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) can be utilized to capture temporal relationships between frames. These layers aid the network in comprehending the movement and path of objects throughout a period.

4. Detection Head: The task of this component is to identify objects within single frames. Generally, it is made up of convolutional layers and then detection layers (like anchor-based or anchor-free detectors), which forecast bounding boxes, objectness scores, and class probabilities for every identified object.
5. Feature Fusion Layer: In multi-object tracking, information from both the current frame and previous frames is crucial. A feature fusion layer combines features from the current frame with features from the previous frames to provide context for object tracking.
6. Temporal Association Module: This module associates object detections across consecutive frames to form tracks. It utilizes techniques such as data association algorithms (e.g., Hungarian algorithm) or Kalman filters to link detections over time while maintaining consistency in object identities.
7. Output Layer: The final output layer provides the tracked object trajectories, usually in the form of bounding boxes with associated object IDs or labels.
8. Loss Function: To train the network, a loss function is employed to measure the disparity between the predicted object trajectories and the ground truth annotations. Common loss functions for multi-object tracking include a combination of localization loss, classification loss, and association loss.





2. LITERATURE REVIEW

Recently, there has been a noticeable surge in interest in automated scoring systems for sports, driven by improvements in computer vision methods and machine learning algorithms. In the field of badminton, there is increasing interest in using computer vision techniques for developing automatic scoring systems. The goal of this literature review is to provide an overview of the latest studies and advancements in the field of computer vision methods for automated scoring systems in badminton.

2.1 Object Detection and Tracking

The development of automatic scoring systems for badminton matches relies heavily on object detection and tracking as crucial components. By utilizing progress in deep learning models, especially Convolutional Neural Networks (CNNs), scientists have achieved substantial progress in instantaneous identification and monitoring of important components like players and shuttlecocks. This literature review gives a summary of important research and methods in the area of badminton object detection and tracking.

1. Deep Learning-Based Object Detection:

- Deep learning models, particularly CNNs, have shown impressive abilities in tasks involving object detection. Research like [1] has employed CNNs to detect players and shuttlecocks in real-time in videos of badminton matches.
- Researchers have reached high accuracy levels in identifying and locating players and shuttlecocks in video frames by training CNNs on annotated datasets of badminton match videos.

2. YOLO (You Only Look Once) for Shuttlecock Detection:

- YOLO (You Only Look Once) algorithm applied for identifying Shuttlecock.
- YOLO is a widely used algorithm for detecting objects, valued for its speed and precision. Researchers have utilized different versions of YOLO, like YOLOv3 [2], to effectively identify shuttlecocks in video frames.
- YOLO's distinct design enables the detection of numerous objects at the same time in one network pass, which makes it ideal for analyzing badminton matches in real-time.

3. Efficient Tracking of Shuttlecock Movement:

- Tracking the movement of shuttlecocks efficiently. It is essential to monitor the shuttlecock's movement during the game in order to keep track of the score. Methods like Kalman filtering and optical flow [3] have been used to monitor the shuttlecock's path in successive frames.
- By constantly adjusting the calculated location of the shuttlecock according to its past path and observed movement, these tracking methods guarantee precise and seamless tracking of the shuttlecock's motion.

4. Integration of Object Detection and Tracking:

- Combining object detection with tracking algorithms allows for continuous monitoring of players and shuttlecocks during the game. Research from [4] has suggested models that integrate CNN-based object detection and Kalman filtering to improve the tracking of shuttlecocks during badminton games.
- This integration guarantees that the system can not just identify players and shuttlecocks, but also track their movements accurately over time, giving a complete insight into the dynamics of the match.

2.2 Court Mapping and Perspective Transformation

Having a bird's-eye view of the badminton court is essential for precise analysis and scoring in automated scoring systems. This viewpoint provides a thorough grasp of the court's spatial arrangement, allowing for efficient monitoring and examination of important aspects like player motions and shuttlecock path. Studies have concentrated on creating techniques for court mapping and perspective transformation through the utilization of geometric algorithms and homography matrices.

Court mapping is the method used to precisely establish the spatial coordinates and dimensions of the badminton court in video frames. This usually involves recognizing important markers on the playing field, like the corners and edges. Geometric algorithms are used next to determine the locations of these reference points in relation to the camera's perspective.

After identifying the reference points on the court, perspective transformation techniques are used to change the video frames into a bird's-eye view of the court. Homography matrices are crucial in this transformation process. A homography matrix is a matrix used to transform points from one perspective (such as the camera view) to another perspective (a top-down view of the court). Applying the homography matrix to the video frames effectively changes the perspective of the images, giving a top-down view of the court.

Converting the video frames to a bird's eye view of the court offers numerous benefits. To start with, it makes future analysis tasks easier by offering a uniform and steady perspective of the court. This makes it easier to analyze the trajectory by accurately tracking and analyzing the shuttlecock's movement in relation to the court's design. Furthermore, it allows for shuttle drop detection by offering a clear visualization of the shuttlecock's landing location on the court.

Additionally, the bird's eye view enables a clearer understanding of the spatial connections among players, shuttlecock, and court limits. This data is essential for correctly assigning points and determining game-time choices.

2.3 Trajectory Analysis and Shuttle Drop Detection

Trajectory analysis and shuttle drop detection are fundamental components of automatic scoring systems for badminton matches. These techniques are essential for accurately tracking the movement of the shuttlecock and identifying crucial events such as shuttle drops, which signal the end of a rally or point. Studies in this area have employed various trajectory analysis techniques to achieve precise detection of shuttle drop events.

Trajectory analysis begins by connecting the positions of the shuttlecock detected in consecutive frames over time. This requires following the path of the shuttlecock by creating a series of points showing where it is at various times in the game. By linking these points together, a path is created showing the shuttlecock's movement on the court.

After setting the trajectory line, different measurements like velocity and orientation can be used to examine the shuttlecock's motion. The shuttlecock's speed plays a crucial role in identifying a shuttle drop, as it reveals the rate at which the shuttlecock descends towards the court. Techniques such as setting a defined speed limit determine when the shuttlecock is considered to be descending.

If the shuttlecock's speed falls below this threshold, it suggests that the shuttlecock is descending rapidly, potentially indicating a shuttle drop event.

Consecutive frame analysis is another technique employed for shuttle drop detection. This method includes analyzing consecutive frames of the video to find moments when the shuttlecock's speed stays consistently slow across several frames. The reason for this method is that continuous slow speeds of the shuttlecock in several frames suggest a shuttle drop occurrence as the shuttlecock moves downward towards the court.

By combining trajectory analysis with techniques such as speed thresholding and consecutive frame analysis, automatic scoring systems can accurately detect shuttle drop events in badminton matches. These techniques enable the system to identify the precise moment when a shuttle drop occurs, allowing for timely attribution of points and accurate tracking of match progress.

2.4 Player Pose Prediction and Activity Recognition:

Anticipating the position of players and recognizing their actions in the game is known as Player Pose Prediction and Activity Recognition.

Anticipating player positions and identifying distinct actions, such as serving movements, are crucial in automated scoring systems for badminton games. These techniques are crucial for accurately determining the beginning of points and allocating points to the correct player based on their gameplay. Recent research has explored the use of Convolutional Neural Networks (CNNs) in predicting player positions, enabling a more detailed analysis of player movements and game events.

CNNs have demonstrated impressive abilities in a range of computer vision jobs, such as identifying objects, categorizing images, and determining poses. CNNs are trained on annotated datasets in badminton, which have images or video frames of players' poses and movements from matches. CNNs learn to identify patterns and features representing different player poses and actions like serving, smashing, and returning the shuttlecock through analyzing annotated data.

After being trained, CNNs can effectively forecast players' positions in real-time while playing badminton. Through studying players' positions, these systems are able to deduce important occurrences like the start of points. For instance, identifying a particular pose linked to a service motion can signal the start of a rally or point during the match. In the same way, being able to identify the actions of other players, like a well-executed smash or a mistake, can help ensure that points are correctly awarded.

Additionally, utilizing CNN for pose prediction allows the system to monitor players' actions and motions during the game. The system can track rallies and detect score points or changes in game status by analyzing player poses consistently, like during a service rotation or change of ends.

Furthermore, the use of CNN-based technology for predicting poses can assist in clarifying uncertain scenarios, such as disagreements regarding line calls or player placements. Through examining the positions of players at particular times in the game, the system can offer referees and officials important information to help them make educated choices and settle disputes.

Table 1: Literature Review Findings

Sr. No	Title	Main Idea/Contribution	Proposed Enhancement
1	Rahmad, Nur & Sufri, Nur Anis Jasmin & As'ari, Muhammad Amir & Azaman, Aizreena. (2019). Recognition of Badminton Action Using Convolutional Neural Network. Indonesian Journal of Electrical Engineering and Informatics (IJEI). 7. 10.52549/ijeii.v7i4.968. [1]	- Integrates open-source Large Language Models (LLMs) with specialized modules—schema mining, schema linking, SQL generation, and a SQL critic module—to enhance the accuracy and usability of converting natural language queries into SQL statements.	-Offer a complete analysis of the match, including scoring, shuttle tracking, and player actions. Provide real-time, data-driven insights to assist referees in making accurate decisions.
2	Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao. 2020. Yolov4: Optimal speed and accuracy of object detection. arXiv preprint arXiv:2004.10934 (2020). [2]	- object detection model that can be adapted for various applications, including sports analytics, by training on domain-specific datasets	- Not tailored for specific sports or applications.. Can Integrate Self-Adversarial-Training (SAT). Improve gradient flow and model accuracy by facilitating deeper network training.

3. METHODOLOGY

Our proposed system consists of several key components, like Shuttlecock detection, custom model for court corner detection to generate homography matrix, trajectory analysis, shuttle drop detection with the help of shuttle speed, custom CNN model for the service prediction, polygon detection for shuttle drop location marking and point prediction.

3.1 Shuttlecock Detection using TrackNetV3:

- Shuttlecock detection is a critical component of the automatic scoring system for badminton matches. TrackNetV3 is specifically designed as a deep learning model for object detection and tracking within video sequences. In the context of badminton, where the shuttlecock's movement is rapid and unpredictable, the efficiency and accuracy of the shuttlecock detection model are paramount.
- TrackNetV3 operates by processing each frame of the video footage individually. By utilizing both CNNs and RNNs, TrackNetV3 can distinguish the shuttlecock in the midst of

the complex game environment. The model has been trained using a large collection of badminton match videos in order to understand and identify patterns related to shuttlecock motion.

- TrackNetV3 excels in its capability to monitor the shuttlecock's path frame by frame in live settings. This indicates that TrackNetV3 constantly adjusts its calculation of the shuttlecock's location as it travels across the court in a game. Through carefully examining every frame, the model guarantees that the system stays in sync with the rapid pace of the game, offering precise and prompt updates on the shuttlecock's location.
- TrackNetV3's advanced capabilities allow it to manage different obstacles often faced in badminton games, such as shifts in lighting, occlusions from players or the net, and changes in the shuttlecock's speed and path. The model's resilience enables it to deliver dependable results in various match situations, ensuring a constant and precise detection of the shuttlecock during the entire game.
- In general, TrackNetV3 is essential in the automated scoring system as it gives live updates on the shuttlecock's location. Its precision in following the shuttlecock's path step by step

guarantees that the system stays synchronized with the progress of the game, ultimately enhancing its efficiency in accurately scoring badminton matches.

Table 2: TrackNet V3 Only V/S TrackNet V3 + Euclidean Distance

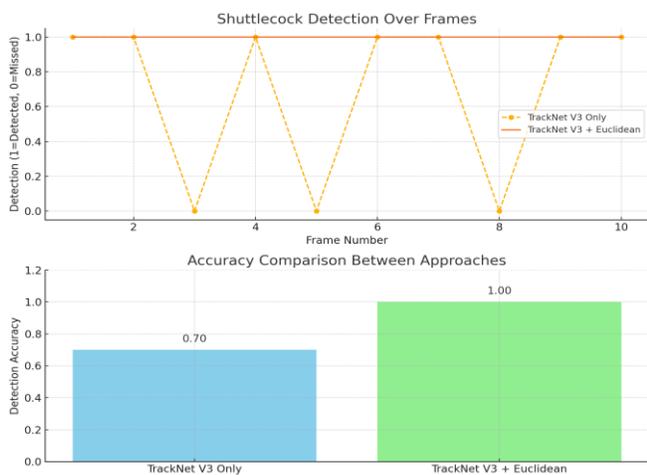
3.2 Custom Model for Court Corner Prediction and Homography Matrix:

- The development of a custom model for court corner prediction and the computation of a homography matrix are crucial steps in achieving a top-view perspective of the badminton court within the automatic scoring system.
- Firstly, let's delve into the custom model for court corner prediction. This model is specifically designed to predict the corners of the badminton court based on the perspective captured in the video frame. By analyzing the visual cues present in the frame, such as the markings on the court and the surrounding environment, the model is trained to accurately predict the locations of the court's corners. This prediction process is essential for establishing a reference frame within the video footage that corresponds to the actual dimensions and layout of the badminton court.
- Once the corners of the court are predicted, the next step involves computing a homography matrix. A homography matrix is a transformation matrix that maps points from one perspective (in this case, the camera view captured in the video frame) to another perspective (a top-down view of the court). By applying the homography matrix to the video frame, the perspective of the image is effectively transformed, providing a bird's-eye view of the badminton court.
- This bird's-eye view simplifies subsequent analysis tasks by presenting the court in a more comprehensible and standardized format. For example, the transformed image allows for easier identification of court boundaries, player positions, and shuttlecock trajectories. This simplification facilitates the accurate tracking and analysis of key elements within the game, ultimately contributing to the overall effectiveness of the automatic scoring system.
- In summary, the custom model for court corner prediction and the computation of the homography matrix are essential components of the automatic scoring system. These components work together to establish a top-view perspective of the badminton court within the video footage, simplifying subsequent analysis tasks and enhancing the accuracy and efficiency of the scoring system.

Criteria	Approach 1: TrackNet V3 Only	Approach 2: TrackNet V3 + Euclidean Distance
Detection Mechanism	Purely relies on deep learning-based object detection	Combines deep learning with mathematical interpolation
Handling Missed Detections	Missed frames are ignored; leads to trajectory discontinuity	Uses Euclidean distance to interpolate and recover shuttlecock coordinates
Accuracy of Shuttlecock Trajectory	May be inconsistent due to missed detections	More consistent and smooth trajectory with gap-filling
Frame Continuity	Frame drops or detection gaps create discontinuity	Maintains continuity by predicting shuttlecock position in missing frames
Robustness in Real-Time Scenarios	Less robust under occlusion or motion blur	More robust, as interpolated values provide backup in failure cases
Ease of Implementation	Easier to implement using existing model	Requires additional logic for distance calculation and prediction
Customizability	Limited to what the model learns	More flexible – custom thresholds and prediction rules can be applied
Overall Detection Accuracy	Moderate, depends solely on model confidence	Improved, especially in challenging frames where model fails

Ideal Use Case	Basic shuttlecock detection in clear frames	Advanced detection in high-speed or partially occluded scenes
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➤ In general, the trajectory analysis is vital to the automated scoring system as it offers important details on the shuttlecock's movement patterns. Through linking regular points on a path to form a line and assessing velocity and orientation on this path, the system can precisely monitor the projectile's movement during the game, improving the overall precision and effectiveness of the scoring system.



3.3 Trajectory Analysis:

- Once the frame has been transformed into a top-view perspective, the system initiates the analysis of the shuttlecock's trajectory, a pivotal step in accurately tracking its movement throughout the match.
- The trajectory analysis begins by connecting the most frequent coordinates of the shuttlecock's position over time. These coordinates represent the successive locations where the shuttlecock has been detected within the transformed frame. Connecting these points forms a trajectory line that visually represents the path of the shuttlecock as it moves across the court.
- The trajectory line is an essential tool for comprehending how the shuttlecock moves in a match. By analyzing the path of the shuttlecock, the system can gather important information about its velocity, course, and general motion patterns.
- A crucial element in trajectory analysis involves measuring the speed of the shuttlecock as it moves along the trajectory line. The system can determine the shuttlecock's velocity at different points throughout the match by measuring the time it takes to move between consecutive points on its path. This data provides important perspectives on the game's speed and energy, allowing for a deeper grasp of the match's dynamics.
- Furthermore, the trajectory analysis enables the system to ascertain the shuttlecock's movement direction on the court. By analyzing the angle and curve of the shuttlecock's trajectory, the system can predict the path and forecast its forthcoming motions. The ability to predict is crucial for accurately monitoring the shuttlecock's path and enabling prompt reactions during the game.

3.4 Shuttle Drop Detection:

- Shuttle drop detection is a critical component of the scoring system, pivotal in accurately determining when points are scored during a badminton match.
- When a player executes a drop shot, the shuttlecock descends rapidly towards the ground with a distinctive change in speed and trajectory. Recognizing this characteristic movement pattern is essential for identifying shuttle drop events and attributing points accordingly.
- The detection process begins by monitoring the speed of the shuttlecock within each frame of the video footage. A predefined threshold speed is established, below which the shuttlecock is considered to be descending. Frames displaying shuttlecock speeds below this threshold are flagged for further analysis.
- To ascertain whether a shuttle drop has occurred, the system examines consecutive frames exhibiting low shuttlecock speeds. The rationale behind this approach is that multiple frames depicting sustained low speeds suggest a consistent downward movement of the shuttlecock. This consistent downward trajectory is indicative of a shuttle drop, signaling the end of a rally or point in the match.
- By systematically analyzing shuttlecock speeds and identifying patterns of sustained low speeds across consecutive frames, the system can reliably detect shuttle drop events with a high degree of accuracy. This enables the scoring system to precisely attribute points to the appropriate player based on the occurrence of shuttle drops, ensuring fair and accurate scoring throughout the match.
- In essence, shuttle drop detection serves as a crucial mechanism for signaling pivotal moments in the match, where points are scored. By leveraging speed thresholds and sequential frame analysis, the system can effectively discern shuttle drop events, contributing to the overall accuracy and integrity of the scoring process in badminton matches.

3.5 Convolutional Neural Network (CNN) for Pose Prediction:

- Using a CNN model to anticipate player positions during serving improves the automatic scoring system's accuracy in monitoring and assigning points in a badminton game.

- The CNN model is educated using a large dataset of labeled images or video frames that show different player positions while serving.
- These poses include specific body orientations, racket positions, and other relevant cues indicative of the initiation of a point.
- During a badminton match, the system continuously analyzes the video feed to detect instances of player service motions. The CNN model is activated to forecast the pose of the player carrying out the service when a service motion is identified. This forecast covers the player's stance, posture, and movement, offering valuable insights into their intentions and actions.
- The system can recognize the start of a point by examining player movements, especially during service actions.
- Service motions typically signify the start of a new rally or point in a badminton match. Therefore, accurately identifying and timestamping these moments is crucial for attributing points correctly and tracking the match's progress.
- Furthermore, the information derived from analyzing players aids in accurately attributing points to the correct player. The system can assign points based on players' performances in each rally by linking particular player poses with specific actions like serving or returning the shuttlecock.
- Furthermore, monitoring player positions throughout the game allows the system to track the evolution of the match and make immediate scoring modifications. For instance, noticing a difference in player positions could signal the end of a rally or the start of a new one, leading the system to adjust the score accordingly.
- By overlaying these polygons on the top-view image of the badminton court, the system creates a visual map of the points scored during the match. Each polygon represents a specific landing location where the shuttlecock has touched the ground, signaling the end of a rally or point.
- These shapes are geometric polygons that enclose the space where the shuttlecock hits the court surface. The polygons' size and shape can change based on factors like shuttlecock detection accuracy and court surface traits.
- The system generates a visual representation of the points scored in the match by superimposing these polygons onto the top-view image of the badminton court. Every shape indicates a distinct spot where the shuttlecock has landed, indicating the conclusion of a rally or point.
- These polygons act as visual cues for referees, giving them a precise summary of the points earned in the game. Referees can quickly decide the exact location where the shuttlecock lands and verify the accuracy of the scoring system's detections.
- Additionally, the polygons improve the viewing experience for spectators, making it easier for them to track the progression of the match. By showing the points scored on the court surface, spectators can gain a clearer grasp of the game's momentum and admire the players' talent and accuracy.
- In general, the accuracy and clarity of the scoring process in badminton matches are improved by creating polygons to indicate shuttlecock landing locations on the top-view image. These shapes help referees keep track of points and make it easier for spectators to follow the scoring process.

3.6 Polygon Creation for Shuttle Drop Location Marking:

- An important part of the automatic scoring system for badminton matches involves outlining polygons on the overhead image to indicate where the shuttlecock has landed. This procedure improves the system's capacity to precisely monitor and display the points earned in the game, making it easier for referees and spectators to score.
- Once the system detects shuttle drop events, indicating that points have been scored, it proceeds to mark the landing locations of the shuttlecock on the top-view image of the badminton court. These landing locations are typically represented as coordinates on the court surface.
- To provide a clear visual representation of these landing locations, the system creates polygons around each detected landing point. These polygons serve as geometric shapes enclosing the area where the shuttlecock makes contact with the court surface. The size and shape of the polygons may vary depending on factors such as the precision of the shuttlecock detection and the characteristics of the court surface.

3.7 Experimental Results:

The experimental evaluation proves the efficiency of the system that is suggested. Performance metrics like accuracy, precision, and recall evaluate how well the system accurately scores badminton matches. Real-life testing situations are carried out to confirm the system's efficiency in different scenarios, including changes in lighting and player movements. The automatic scoring system provides a complete solution for accurately scoring badminton matches by integrating these components with computer vision techniques.

4. CONCLUSION

In summary, our research introduces a cutting-edge automatic scoring system tailored specifically for badminton matches, leveraging the power of computer vision techniques. Through the integration of sophisticated algorithms, our system tackles key aspects of the scoring process, including shuttlecock detection, court mapping, trajectory analysis, and player pose prediction. Firstly, our system employs state-of-the-art algorithms, such as TrackNetV3, for precise detection of the shuttlecock's movements within the video footage. This ensures accurate tracking of the shuttlecock's position throughout the match, forming the foundation for reliable scoring. Additionally, we have developed a custom model to predict the corners of the badminton court, enabling the creation

of a homography matrix. This matrix facilitates the transformation of the video frame into a top-view perspective, simplifying subsequent analysis tasks and enhancing accuracy. Furthermore, trajectory analysis techniques are applied to track the shuttlecock's movement patterns over time. By connecting frequent coordinates, our system accurately measures the shuttlecock's speed and direction, providing valuable insights into the dynamics of the game. Moreover, we integrate a convolutional neural network (CNN) model for predicting player poses during service. This enables us to determine the initiation of points with precision, further enhancing the accuracy of our scoring system.

In the future, we will concentrate on improving and enhancing the system for increased accuracy and efficiency. We also intend to investigate possible uses in live match broadcasting and coaching analytics by utilizing our automated scoring system to offer instant insights and improve the overall experience for players, coaches, and spectators.

5. REFERENCES

[1] Rahmad, Nur & Sufri, Nur Anis Jasmin & As'ari, Muhammad Amir & Azaman, Aizreana. (2019). Recognition of Badminton Action Using Convolutional

Neural Network. Indonesian Journal of Electrical Engineering and Informatics (IJEEI). 7. 10.52549/ijeei.v7i4.968.

[2] Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao. 2020. Yolov4: Optimal speed and accuracy of object detection. arXiv preprint arXiv:2004.10934 (2020).

[3] Nikolskaia, A. & Goncharov, Pavel & Ососков, Геннадий & Rezvaya, E. & Rusov, D. & Shchavalev, E. & Baranov, D.. (2021). TrackNetV3 WITH OPTIMIZED INFERENCE FOR BM@N TRACKING. 332-337. 10.54546/MLIT.2021.67.13.002.

[4] Mohammad Esfandiarpour, Seyed Mani Mirshabani, Ehsan Maani Miandoab, "Ball Detection Algorithms Enhancement in Sport Robots", *2024 13th Iranian/3rd International Machine Vision and Image Processing Conference (MVIP)*, pp.1-6, 2024.

[5] Dhananjay Kumar Yadav, Neeraj Kumari, Syed Harron, "Advances in Convolutional Neural Networks for Object Detection and Recognition", *2024 International Conference on Optimization Computing and Wireless Communication (ICOCWC)*, pp.1-6, 2024.

