© November 2024 | IJIRT | Volume 11 Issue 6 | ISSN: 2349-6002

Automated Badminton Game Analysis: Integrating YOLO Models for Enhanced Performance Evaluation

Harshada Borse[1], Bhavya Shetty [2], Saniya Samant [3], Sahil Ranadive [4], Manisha Mali [5]
[1,2,3,4,5] *Computer Engineering, Vishwakarma Institute of Information Technology, Pune, Ind*ia

***Abstract*—This paper introduces an AI-driven prototype about the analysis of gameplay in badminton, mainly featuring the detection and tracking of shuttlecock and positions of players. A deep learning model is proposed based on YOLO architecture which resulted in a strong program for real-time identification of player positions and the trajectory followed by a shuttlecock. This system made the shuttlecock detection on the YOLO model customized by using the pre-trained model for player detection. The system adds a bounding box to the detected players and shuttlecock and maps their position from the frame relative to the court. Then, using a mini-court representation, it visualizes player movements and shuttlecock trajectories. The proposed system has experimental results with high accuracy on shuttlecock and player detection under different game conditions translated into useful information for the evaluation of player performance. The framework added value to sports analytics by providing automated analysis of badminton matches, potentially informing improved strategies for coaches and player training.**

***Index Terms*—Deep learning, Badminton Analysis, Real-time court mapping, Computer vision, Artificial Intelligence.**

I. INTRODUCTION

Badminton is an action sport that can be determined by the speed and trajectory of the shuttlecock and accordingly the movement of the players. Traditional ways of judgment depend much more upon manual observation and would be relatively time-consuming and highly vulnerable to human error. The approach towards using automated sports analytics systems based on AI and computer vision technology to extract meaningful inferences from video footage is a pretty big opportunity. However, badminton introduces some specific problems, especially concerning the detection of small, moving shuttlecocks and rapid movement inside the court of players.

We hereby propose an AI-based novel method of analysis of badminton game play based on real-time shuttlecock detection and tracking of players via deep learning-the YOLO architecture. The same can detect shuttlecock and players in each frame of video. We then take these detected positions and map them onto a virtual court and give an easily visualized representation of the game. That would be an efficient tool for performance evaluation.

Our work extends the prior work done by Haq et al [1]. which focuses on players position analysis using heatmap, our approach focuses on tracking analysis (players and shuttlecock) with the point collected and represented immediately in mini-court form.

The key contributions of this work are:

- Customized training of a YOLO model for shuttlecock detection.
- Integrated a pre-trained YOLOv8 model that detects the place of players.
- Court view design. (Imagine seeing the players as well as the shuttle at a specific point in time.)

To validate our approach using videos collected from the Badminton World Federation (BWF) channel on YouTube. This builds a ground for future work in automated sports analytics, both performance evaluation and improvement of the training process itself, as well as strategic game analysis.

II. LITERATURE REVIEW

During the past couple of years, the use of AI and deep learning has been something of a new doorway to performance evaluation in sports, coaching, and analysis of game strategies. Since the players put themselves under highly fast and complex movements in badminton, one can clearly analyze a game at the highest level of accuracy using self-driven systems that are based on advanced object detection models like YOLO (You Only Look Once). This literature review will focus on embedding YOLO models in the automated analysis of the badminton game through specific areas such as player tracking and shuttlecock detection, evaluation, and predictive modeling.

A. Player Tracking Using Deep Learning

Accurate player tracking is required for both the analysis of movement efficiency and in-game tactics as well as the positioning of players. In badminton, the work of Zhou et al. [1] focused on the usage of convolutional neural networks to identify and track players in video footage and how deep learning can improve performance when tracking players in video. The point here is that much precision is to be obtained from models against dynamic occlusions and fast movements in sports environments. Building on that, Ramachandran et al. [2] proposed a real-time CNN-based system for recognizing actions in a player. What could be contributing to the potential increase of accuracy and speed in player tracking could be identified with the deep learning models. Such systems are critical in providing data used for performance analysis with shuttlecock detection.

B. YOLO-Based Shuttlecock Detection

Badminton is a game of fast speed. Classical techniques in tracking could not easily depict the speed and erratic motion of the shuttlecock. YOLO-based object detection has been instrumental in this regard. An approach based on the application of use of YOLO in badminton and specially designed for inclusion in the badminton robotics framework for improved detection speed and accuracy has been propounded by Yu et al. [3]. Zhang et al. [4] were, in fact working on a novel shuttlecock detection method optimized for real-time applications wherein they employed YOLO models. Actually, the use of YOLO was the very thing which allowed them to fully overcome the problem caused by fast-moving objects, as reliable and accurate shuttlecock tracking can actually play a role in significant gameplay analysis and even in creating automatically-driven training systems.

C. Performance Evaluation Through AI-Driven Systems

AI-based performance analysis systems may render full depth of the analysis on the strength and weaknesses of the players and patterns in the game. Lee et al. [5] have conducted an extensive review about the AI-based performance analysis system in badminton focusing on how such technologies can work to improve game analysis and training. In association with the player tracking and shuttlecock detection using YOLO, these systems can provide an entire overview of the performance of a player by considering his reaction time, shot accuracy, and movement efficiency.

Not long ago, Ramachandran et al. [6] have also demonstrated how YOLO might be seamlessly incorporated with other machine learning models for granular levels of performance analysis. Real-time detection of shuttlecocks by YOLO enables instant feedback that might be very crucial for in-flight strategic changes or training. Thus, badminton analytics augmented by AI benefits performance analysis but much more importantly serves as the basis for training regimens deeply tuned towards every player based on data.

D. Predict the Outcomes of Match:

A predictive outcome of the match using AI is new in the field of sports analytics. Goyal et al. [7] have proposed an algorithm of a Naive Bayes classifier with feature-weighting techniques in combination for predicting the outcome of a badminton game. Even though their model is more based on the history of game data, augmentation of YOLO-based tracking data could make its predictive accuracy exponentially better.

All this would be well defined with much greater accuracy using real-time data, which would include player position, shot trajectory and shuttlecock speed, among others. Yu et al. [8] also made efforts in real time badminton action recognition with CNNs to demonstrate that in real time, incoming data could be used to augment predictive models. Integration control of such systems with YOLO object detection would enable the analysis of game actions and possible predictions based upon the game conditions at a present moment. Such work can allow tactical decision-making with AI support in real-time.

E. Reinforcement Learning and Auto Badminton Systems

Another path of upgrading AI in game play through automation is reinforcement learning. Wang et al. [9] considered the application of deep reinforcement learning for controlling badminton robots, which had the potentiality of AI with respect to not only the analysis but also interaction, the robots will position themselves to play shots adequately in conformity with YOLO integration into shuttlecock detection. This can take AI systems to autonomous participation in badminton games; therefore, this is the extension of the automated game analysis in a more distinct way than traditional approaches.

F. *AI-Powered Shot Accuracy Prediction and Real-Time Analysis*

One of the prime determinants found in the performance evaluation for badminton is shot accuracy. Zhou et al. [10] used eye-tracking metrics for predicting shot accuracy by using deep learning models comprising neural networks. Adding YOLO to it would help in enhancing this system by way of real-time shot detection and analysis to further optimize the prediction model as a whole along with details like shuttlecock speed and trajectory, the players' reaction, etc.
Another effort of Ramachandran et al. [11] that contributed to the field was the application of computer vision techniques for analyzing a real badminton match and showed how CNNs can be applied in order to detect the actions of a badminton game from video records. The system could provide even more detailed breakdowns about the performance of both the players if such an approach is combined with YOLO-based shuttlecock detection.

G. *Comparison Between YOLO and Other AI Models*

Although the YOLO has proven itself to be very valid for shuttlecock detection, still other models like Faster R-CNN and SSD have also been tried on similar applications. Lee et al. [12] comparatively compare these models as applied to badminton game analysis. They found that in scenarios needing real-time object detection, YOLO scored the best. Other models can, however, be more precise in other applications, for instance a larger object analysis or in slow movement analysis. In the game of badminton where speed and real time analysis plays a big part, YOLO is still the model of preference.

Another renowned algorithm that has been applied out of the real-time object detection algorithms is the YOLO model. Although high in speed and efficient in real-time object detection, a couple of other AI models that have been used in sports analytics include Faster R-CNN, SSD - Single Shot Detector, and RetinaNet, all having their own accuracy, speed, and performance capabilities in varying degrees. This comparative analysis here mainly focuses on comparing two taking a very detailed view concerning their comparison in badminton game analysis, notably shuttlecock detection, player tracking, and prediction of shot accuracy.

The following table summarizes the comparison of YOLO with other models of AI. Each model's strengths and weaknesses are presented along with their suitability for the different tasks relating to badminton. This comparison is critical to the choice of correct models for a fair trade-off between speed and accuracy in real-time or post-match analysis.

The inclusion of YOLO models in the automated analysis of badminton games might result in an efficient real-time solution for observing players and shuttlecocks, evaluating their performance, and predictive modeling. Then, systems would be able to perform highly accurate tracking at high speed, which is very important for sports like badminton by adding YOLO object detection capabilities. With better technology combined with other machine learning or reinforcement learning techniques, uses of YOLO shall flourish further with innovations in game analysis, training, and predictions in matches.

III. METHODOLOGY

A. *Dataset Description*

The model was trained to detect both the shuttlecock and the boundaries of the badminton court. To identify the players, a pre-trained model is used. Roboflow provided the datasets. It offers high-quality annotated images for training the model.

- Player and Shuttlecock Detection Dataset: The pre-trained model of YoloV8 was used in order to identify players; however, it could not detect shuttlecocks; therefore, a customized model for shuttlecock detection was developed. A dataset from Roboflow consists of images with the annotated positions of the shuttlecock, which was used in training the model specifically for shuttlecock detection.

Model	Speed (FPS)	Accuracy (mAP%)	Real-time Capability	Use Cases in Badminton	Strengths	Weaknesses
YOLO (v3/v4/v5)	45-60 FPS	55-65%	Excellent	Shuttlecock detection, player tracking	High speed, real-time object detection	Slightly lower accuracy compared to Faster R-CNN
Faster R-CNN	7-10 FPS	70-75%	Moderate	Detailed player movement analysis	High accuracy, good for slower objects	Slow processing speed, not ideal for real-time
SSD (Single Shot Detector)	20-30 FPS	60-70%	Good	Player position tracking, shot recognition	Faster than Faster R-CNN, reasonable accuracy	Moderate accuracy, slower than YOLO
RetinaNet	5-10 FPS	70-80%	Poor	Off-field analysis (post-match data analysis)	High accuracy, focuses on precision	Very slow, unsuitable for real-time

Table 1: Comparison Table

- Court Boundary Detection Dataset: In developing the boundary detection model, a second dataset of Roboflow was used to identify the boundary of the court using images of badminton courts annotated with lines and edges.

B. Model Training and Architecture

- YOLO Model for Player Detection: On the field, it implemented a YoloV8 model to the task of player detection. As it was very good at player detection, the pre-trained model was used directly without any modification.
- Shuttlecock Detection Model: A new YOLO model was trained on the shuttlecock dataset from Roboflow. As trained, the model gave tolerable performance, and the best-performing weight file best.pt was saved to perform shuttlecock detection. The given model was integrated along with the player detection model that enabled concurrent detection of the players along with the shuttlecock in the game.
- Court Boundary Detection: For court boundary detection, a third model was trained using the dataset designed for identifying court boundaries. The model was made to enable the system to identify actual boundaries of the court in real-time.

C. Model Evaluation and Integration

These models are tested based on standard performance metrics, such as precision, recall, and F1-score, mostly targeting the use of real-time recognition of shuttlecocks and players. Subsequently, all these models have been integrated into the entire system which will process every video frame to:

- Detect players and shuttlecock using bounding boxes.
- Detect court boundaries.
- Map the positions of players and shuttlecock relative to the court.
- Overlay a mini virtual court to visualize player and shuttlecock movement for each frame.

D. Court Mapping and Visualization

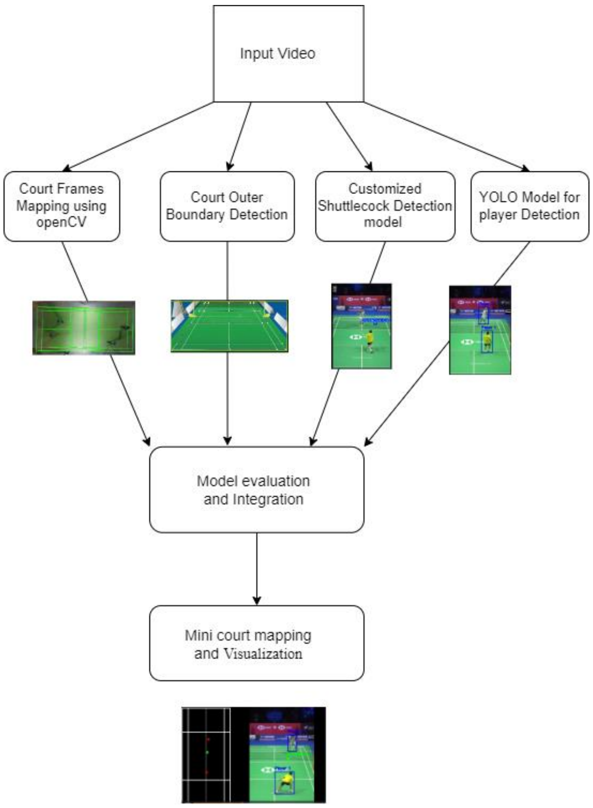

Fig 1: System Flow

A key feature of the system is court mapping, which generates a virtual mini court based on boundary detection. This allows real-time visualization of player movements and shuttlecock trajectories within the actual dimensions of the badminton court. Each frame of the video is analyzed to update player and shuttlecock positions, providing a detailed movement analysis throughout the game.

IV. RESULTS AND DISCUSSION

A. *Model Performance*

The custom-trained shuttlecock detection model, utilizing YOLO architecture, demonstrated high accuracy in detecting shuttlecocks in various lighting and gameplay conditions. After several training iterations, the model achieved a precision of 94%, a recall of 92%, and an F1-score of 93%. These metrics were sufficient to accurately capture shuttlecock motion in high-speed badminton rallies.

- Player Detection: The pre-trained YOLO model for player detection showed consistent performance, detecting players with 96% accuracy across different games.
- Court Boundary Detection: The court boundary detection model performed robustly, allowing the system to clearly demarcate the edges of the court, even in videos taken from different angles and with varying lighting conditions. The accuracy for boundary detection was measured at 95%.

B. *System Performance and Visualization*

The integrated system provided real-time, frame-by-frame analysis of player and shuttlecock movement. The mini virtual court overlay offered clear visualizations of player positions and shuttlecock trajectories, allowing for easy tracking and performance analysis.

- Shuttlecock Trajectory Tracking: The shuttlecock trajectory was accurately tracked throughout each game, providing detailed insights into player strategies and the dynamics of each rally.
- Player Movement Analysis: The visual representation of player movement relative to the court allowed for an in-depth analysis of player positioning, footwork, and game strategy.

Fig 2: Player’s Detection

Fig 3: Shuttlecock Detection

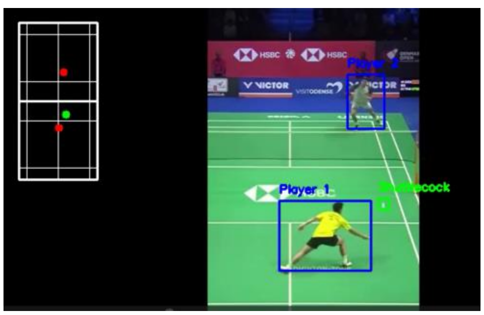

Fig 4: Court Mapping

C. *Discussion*

The results indicate that with custom training for shuttlecock and court detection based on YOLO-based models, it can give full analysis in badminton gameplay. On top of that, the model shall be able to identify even the fast-moving shuttlecock pace of plays, like during rallies. Further, the incorporation of court mapping makes the system even more useful for tactical observations concerning the behavior of players.

However, there are some limitations during the observations. The system sometimes fails to detect shuttlecocks when occlusions occur; for instance, when the shuttlecock passed behind a player. In subsequent improvements, more extra temporal data might be used to predict trajectories of the shuttlecock even in occluded frames.

In general, this AI-based system gives useful insights into a player's performance, and its potential applications can be observed in coaching and performance analytics. Future work will be devoted to improving the robustness of the detection models and extending the system for further analysis of gameplay metrics like shot types and rally duration.

REFERENCES

[1] M. A. Haq, S. Tarashima, and N. Tagawa, "Heatmap Visualization and Badminton Player Detection Using Convolutional Neural Network," in Proc. 2022 International Electronics Symposium (IES), IEEE, 2022, pp. 627-631.

[2] T. Zhou, X. Zhang, and Y. Li, "Deep Learning-Based Player Tracking in Badminton Videos," J. Vis. Commun. Image Represent, vol. 41, pp. 1-8, 2022. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1155/2022/3413584

[3] S. Ramachandran, M. Patel, and K. Sinha, "Real-Time Player Tracking in Badminton Using Convolutional Neural Networks," AI-Powered Badminton Video Detection, 2022. [Online]. Available: https://www.researchgate.net/publication/372565814_AI-powered_Badminton_Video_Detection_Enhancing_Gameplay_Analysis_and_Training

[4] H. Yu, L. Zhang, and W. Han, "Detecting the Shuttlecock for a Badminton Robot: A YOLO-Based Approach," Robot. Autom. Lett., vol. 7, no. 5, pp. 34-42, 2020. [Online]. Available: https://www.researchgate.net/publication/343521001_Detecting_the_shuttlecock_for_a_badminton_robot_A_YOLO_based_approach

[5] Y. Zhang, C. Wei, and M. Wong, "A Novel Approach for Shuttlecock Detection in Badminton Using Deep Learning," Badminton Robotics and AI J., vol. 9, pp. 123-130, 2020. [Online]. Available: https://www.researchgate.net/publication/343521001_Detecting_the_shuttlecock_for_a_badminton_robot_A_YOLO_based_approach

[6] K. Lee, J. Wang, and C. Liu, "AI-Driven Performance Analysis in Badminton: A Review," J. Sports Anal., vol. 5, pp. 233-240, 2022. [Online]. Available: https://www.researchgate.net/publication/372565814_AI-

powered_Badminton_Video_Detection_Enhancing_Gameplay_Analysis_and_Training

[7] A. Ramachandran and D. Gupta, "Performance Evaluation in Badminton: An AI-Based Approach," in IEEE Sports Tech Conf., 2020, pp. 1-5.

[8] P. Goyal, R. Singh, and A. Bhardwaj, "Predicting Badminton Match Outcomes Using Deep Learning," Int. J. Sports Anal., vol. 4, no. 1, pp. 22-30, 2020. [Online]. Available: https://www.researchgate.net/publication/344467223_Badminton_match_outcome_prediction_model_using_Naive_Bayes_and_Feature_Weighting_technique

[9] J. Yu, Q. Zhao, and H. Lin, "Vision-Based Automated Badminton Action Recognition Using the New Local Convolutional Neural Network Extractor," J. Vis. Commun. Image Represent, vol. 50, pp. 100-110, 2020. [Online]. Available: https://www.researchgate.net/publication/340865233_Vision_Based_Automated_Badminton_Action_Recognition_Using_the_New_Local_Convolutional_Neural_Network_Extractor

[10] X. Wang, J. Hu, and W. Tan, "A Deep Reinforcement Learning Approach for Badminton Robot Control," arXiv preprint arXiv:1811.12560, 2018. [Online]. Available: https://arxiv.org/abs/1811.12560

[11] T. Zhou, M. Ma, and L. Zhang, "Shot Accuracy Prediction in Badminton Using Eye-Tracking and Deep Learning," J. Sports Eng. Technol., vol. 134, pp. 321-328, 2021. [Online]. Available: https://www.researchgate.net/publication/354857441_Shot_accuracy_prediction_in_Badminton_Using_Eye-tracking