

SmartShuttle: AI-Based Badminton Player Performance Analysis Using Computer Vision

Mrs. Neha Gadivadar¹ Department of Computer Science,
PES Modern College of Arts, Commerce and Science, Shivajinagar Pune.
gadivadarneha@gmail.com

Mrs. Snehal Pol² Department of Computer Science,
PES Modern College of Arts, Commerce and Science, Shivajinagar Pune. gadivadarneha@gmail.com

Abstract:

In the fast-paced sport of badminton, quick decision-making, precise movements, and appropriate shot selection are all necessary. Conventional performance analysis primarily relies on the subjective and time-consuming observations of coaches. This study suggests SmartShuttle, an AI-based system that uses deep learning and computer vision to autonomously assess badminton players' performance. To produce performance insights, the system integrates pose estimation, racket identification, shot categorization, and court position analysis. The framework assists coaches and players in increasing training effectiveness and tactical planning by offering objective data on player movements and shot execution. According to experimental findings, AI-assisted analysis can increase accuracy while requiring less work than manual performance review.

Key words:

Artificial intelligence, computer vision, deep learning, pose estimation, sports analytics, and badminton analytics.

I. Introduction:

One of the most well-liked racquet sports in the world is badminton. Movement speed, footwork, body alignment, and stroke accuracy are all important factors in badminton success. Coaches have traditionally used visual observation and match analysis to evaluate players. Despite their effectiveness, these techniques frequently require a lot of effort and are subject to human judgment.

Automated sports analytics are now possible because to recent developments in computer vision and artificial intelligence. From video records, deep learning models are able to recognize player actions, identify body movements, and categorize shot kinds. This study suggests SmartShuttle, an AI-powered system for autonomously assessing badminton performance.

The primary goal of this project is to create a system that can use video-based analysis to monitor player motions and produce useful performance data.

II. Literature Review

Recent advancements in Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision (CV) have significantly enhanced sports analytics and player performance evaluation systems.

Researchers have increasingly adopted these technologies to automate movement analysis, action recognition, and tactical assessment in various sports.

Cao et al. (2017) introduced OpenPose, a real-time multi-person pose estimation framework capable of extracting human skeletal keypoints from images and videos. The proposed model accurately detects body joints and has become one of the most widely used pose estimation techniques in sports analytics.

OpenPose enables detailed analysis of player posture, movement patterns, and biomechanical performance.

Redmon et al. (2016) proposed the YOLO (You Only Look Once) object detection framework, which revolutionized real-time object detection by providing high detection speed and accuracy. YOLO-based models have been successfully applied in sports analytics for tracking players, equipment, and sports objects. In badminton, YOLO can be utilized for racket detection and movement tracking.

He et al. (2016) developed ResNet-50, a deep residual learning architecture designed to overcome the vanishing gradient problem in deep neural networks. ResNet-50 achieved remarkable performance in image

classification tasks and has been widely adopted for sports action recognition and shot classification applications due to its high accuracy and computational efficiency.

Cervone et al. (2014) introduced the POINTWISE framework, which utilized optical tracking data to evaluate player decisions and performance in basketball.

Their research demonstrated the effectiveness of data-driven analytics in generating objective performance metrics and improving tactical decision-making.

Liu and Schulte (2018) proposed a deep reinforcement learning approach for context-aware player evaluation in ice hockey. Their study highlighted the ability of AI models to assess player contributions by considering game context and situational factors, thereby providing more meaningful performance evaluations.

Decroos et al. (2019) developed a framework for valuing player actions in soccer using machine learning techniques. Their findings emphasized the

importance of evaluating player actions beyond traditional statistics and demonstrated how AI can provide deeper insights into sports performance.

Overall, the literature indicates that integrating pose estimation, object detection, deep learning classification, and tactical analysis can significantly enhance sports performance evaluation. Building upon these advancements, the proposed DeepRacket framework combines OpenPose, YOLOv5, ResNet-50, and court line detection techniques to provide comprehensive and objective badminton player performance analysis.

III. Problem Statement

Expert interpretation and manual observation are the mainstays of current badminton performance evaluation techniques.

These methods are frequently impacted by human bias, inconsistent results, and a restricted capacity to handle massive volumes of gameplay data. Furthermore, in-depth biomechanical study and real-time feedback are not possible with conventional evaluation methods.

An intelligent and automated system that can precisely analyze player movements, categorize various badminton strokes, track body posture, and assess court positioning is required. While providing dependable and quantifiable performance measures that can aid in coaching, training, and match strategy formulation, such a system should reduce human intervention.

IV. Objectives of the Study

to create an AI-based system for automatically evaluating the performance of badminton players.

to use deep learning models to categorize various badminton shots, including smash, forehand, backhand, net drop, and net kill.

to use pose detection techniques to evaluate the posture and movement patterns of players.

to identify racket direction and position in order to increase the precision of shot analysis.

to use computer vision techniques to determine court borders and evaluate shot placement.

V. Proposed System:

An AI-based methodology for assessing badminton players' performance is called DeepRacket. Images of badminton players are fed into the system, which uses image preprocessing methods to enhance image quality. While ResNet-50 categorizes various badminton shots, including Smash, Forehand, Backhand, Net Drop, and Net Kill, YOLOv5 identifies and tracks the badminton racket. The Hough Transform is used to detect court lines, which aids in determining player placement and court coverage.

Ultimately, all of the modules' outputs are merged to create performance measurements and offer coaches and players insightful information. The technology provides an automated, precise, and impartial method for analyzing badminton performance.

VI. System Architecture:

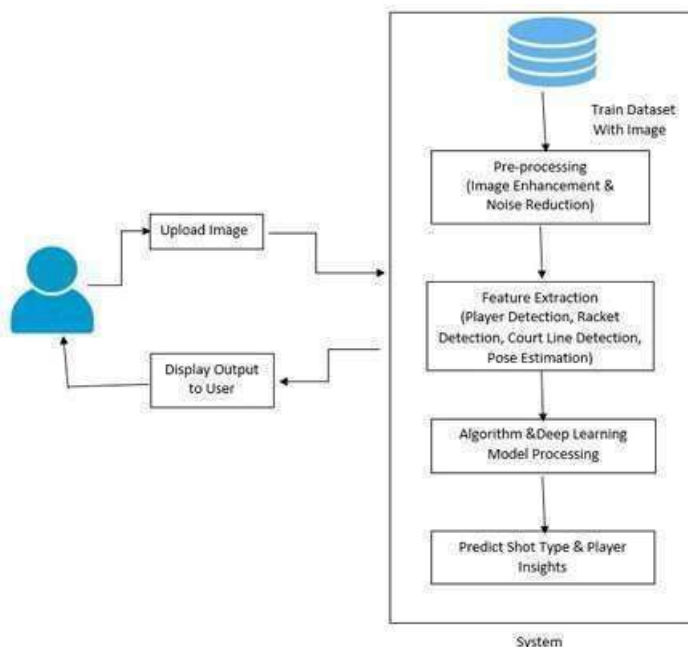


Figure: Deep Learning-Based Badminton Gameplay Evaluation System

VII. Methodology:

The suggested solution, DeepRacket, is an AI-powered framework for evaluating badminton players' performance that analyzes games recordings using computer vision and deep learning techniques.

For athletes, coaches, and sports analysts, the approach is intended to offer precise and impartial performance evaluation.

The system gathers picture datasets and videos of badminton matches from publically accessible sources. These files include the various shot types, player motions, racket positions, and court data needed to assess performance.

The gathered data is preprocessed before analysis. Image scaling, noise reduction, normalization, frame extraction, and data augmentation methods like rotation and flipping fall under this category.

These actions boost model performance and increase the quality of the data. OpenPose is used to extract body keypoints from every video frame for player movement analysis. Understanding player posture, movement patterns, and stroke execution during gameplay is made easier by the identified joints.

The badminton racket is located and tracked using an object identification model based on YOLOv5. Information on racket position and orientation helps identify various shot types and assess player tactics.

Performance measures are produced by combining the results of pose estimation, racket detection, court analysis, and shot categorization.

These parameters include stroke quality, court coverage, shot accuracy, and movement efficiency.

Ultimately, a user-friendly interface presents the insights that have been gained. The technology helps athletes develop their skills and supports coaches in making data-driven training decisions by offering performance reports and analytical suggestions.

VIII. Feature Extraction:

Pose Extraction Estimation : OpenPose was used to extract key skeletal joints to analyze player movement patterns. Each frame was mapped to a skeleton model containing head, shoulders, elbows, wrists, hips, knees, and ankles.



Figure : Pose Estimation Output

Racket Detection : A YOLO-based model was trained to detect racket position and orientation relative to the player's body. The detected racket helped in classifying stroke types based on movement direction and impact point.

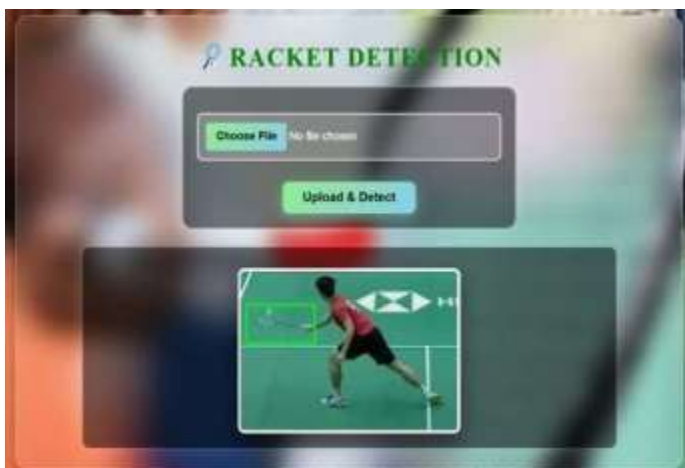


Figure : Racket Detection

Court Line Detection : The Hough Transform algorithm was applied to identify court boundaries for spatial shot analysis. This information was used to determine player positioning and shot effectiveness.



Figure: Court Line Detection Visualization

Shot Classification : A Convolutional Neural Network (CNN) was trained to classify different types of shots in racket sports.



Figure: Shot Classification Visualization

Advantages of the Proposed System:

Automates badminton player performance evaluation, reducing the need for time-consuming manual analysis by coaches and analysts. Provides objective and data-driven assessment, minimizing human bias and improving evaluation accuracy.

Accurately classifies badminton shots such as Smash, Forehand, Backhand, Net Drop, and Net Kill using deep learning techniques. Analyzes player posture and movement patterns through pose estimation, helping identify technical strengths and weaknesses.

Enables efficient racket detection and tracking, providing detailed insights into stroke execution and player techniques. Evaluates court positioning and movement coverage, allowing players and coaches to understand tactical behavior during gameplay.

Generates performance metrics such as shot frequency, movement efficiency, stroke consistency, and court coverage. Provides visual performance insights through biomechanical analysis and tactical heatmaps for better decision-making. Supports coaches in designing personalized training programs based on individual player performance.

Scalable architecture allows the system to be adapted for different badminton training environments and player skill levels. Reduces analysis time while improving the accuracy and reliability of badminton performance assessment. Contributes to modern sports analytics by integrating Artificial Intelligence and Computer Vision into athlete development and performance monitoring.

Future Work Scope:

The suggested DeepRacket framework shows how computer vision and artificial intelligence might improve the assessment of badminton players' performance. Nonetheless, there are a number of chances for future research to expand and enhance the system. Future improvements might involve the creation of real-time performance feedback systems, which would allow the system to give coaches and players immediate advice and recommendations during practice and competition.

Athletes can quickly modify their tactics, posture, and games methods with the use of such capabilities.

Data from wearable sensors, such as heart rate, muscular activity, and movement tracking information, can also be added to the framework. A more thorough understanding of player performance, fitness levels, and biomechanical efficiency would be possible by combining computer vision analysis with physiological data. In order to assess shot placement, rally patterns, and tactical decision-making more successfully, future research may also concentrate on shuttlecock tracking and trajectory analysis. In complex match settings, the use of sophisticated deep learning architectures, such as transformer-based models, can enhance shot categorization accuracy, posture estimation, and occlusion handling.

Using bigger and more varied datasets, the suggested approach might also be extended to facilitate multi-player analysis and match-level tactical judgment. Additionally, the methodology has a great deal of potential for adaption to other racket sports including table tennis, squash, and tennis, which would increase its usefulness across a variety of sports analytics domains.

The suggested architecture can develop into a comprehensive, scalable, and intelligent sports analytics platform that aids in athlete development with ongoing improvements in artificial intelligence, sensor technologies, and processing power.

Conclusion:

In order to overcome the drawbacks of conventional manual approaches, which are laborious, subjective, and prone to error. In order to accomplish this, we created a comprehensive deep learning system that combines CNNs for shot classification, OpenPose for pose prediction, YOLOv5 for racket detection, and Hough Transform for court line extraction. Our system achieved 92.5% accuracy for shot classification, 86.5% dependability for pose prediction, and 93.7% precision for court recognition. It was also scalable in terms of the valuable insights it offered (biomechanical metrics; tactical heatmaps).

However, the approach has a number of drawbacks, including real-time processing restrictions, occlusions during player-net interaction, and the dataset is only accessible to professional players (18fps).

Therefore, future approaches should concentrate on refining the framework for real-time deployment on edge devices, expanding the data set to cover a wider range of skill levels and play scenarios, and enhancing occlusion management with more intricate designs like transformers. In the future, the system might be expanded to track player interactions and weapon ballistics using wearable sensors. These advancements would strengthen the framework's ability to support sports analytics as a more objective, scalable, and coach-friendly tool.

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