2nd INTERNATIONAL CONFERENCE ON RESEARCH PERSPECTIVES IN NEW-GEN COMPUTATIONAL PARADIGMS (ICRPNCP 25)

12th & 13th August 2025

PROCEEDINGS

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Certified by ISO 9001:2015

Kangayam Road, Tirupur - 4

Tamil Nadu, India.

 ISBN: 9-788199-007819

Optimizing Performance Evaluation of Badminton Players using Proximal Policy Optimization (PPO) Algorithm

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Abstract:
Badminton performance evaluation has traditionally relied on subjective coaching assessments and basic statistical metrics, limiting scalability and real-time feedback. This study proposes a novel framework leveraging Proximal Policy Optimization (PPO)—a reinforcement learning (RL) algorithm—to automate and enhance player performance analysis through data-driven decision-making. By integrating multi-modal inputs (computer vision for shuttle tracking, feedback from players and match statistics), the system trains PPO agents to evaluate tactical choices (e.g., shot selection, footwork efficiency) and strategic adaptability during rallies [1]. The PPO-based model dynamically optimizes a reward function that quantifies player strengths and weaknesses, balancing short-term actions (e.g., smash effectiveness) with long-term game outcomes (e.g., rally win probability). Key performance metrics include a Player Skill Score (PSS)—a composite AI-generated rating—and policy convergence speed, demonstrating PPO's superiority in stability and adaptability. Additionally, the system enables opponent modeling and personalized training recommendations by simulating adversarial strategies. Results show that the PPO-driven system outperforms traditional evaluation methods in accuracy and granularity, as verified by coach assessments. This work bridges sports science and AI, offering a scalable, objective tool for badminton performance optimization, with potential extensions to other racket sports.

Keywords: Reinforcement Learning, PPO, Badminton Analytics, Sports AI, Multi-Modal Data Fusion

I. INTRODUCTION

Badminton is a high-speed racket sport requiring agility, tactical intelligence, and precise shot execution. Traditional performance evaluation relies on manual coaching assessments and basic statistical metrics (e.g., smash success rate, unforced errors), which are often subjective and lack real-time adaptability. With advancements in Artificial Intelligence (AI) and Reinforcement Learning (RL), there is an opportunity to automate and enhance player performance analysis using data-driven approaches [2].

Proximal Policy Optimization (PPO)—a state-of-the-art RL algorithm—has shown success in dynamic decision-making tasks due to its stability and sample efficiency. Applying PPO to badminton analytics can enable real-time tactical feedback, automated skill assessment, and personalized training recommendations. By integrating multi-modal data sources (computer vision for shuttle tracking, inertial sensors for biomechanics, and match statistics), an AI-driven system can evaluate player performance more objectively than traditional methods.

Research Objectives

This study aims to:

- Develop a PPO-based framework for evaluating badminton performance using reinforcement learning.
- Incorporate multi-modal data fusion (vision, sensors, and match logs) to assess technical and tactical aspects.
- Design a dynamic reward function that quantifies in-game decisions (e.g., shot selection, movement efficiency).
- Benchmark PPO against other RL methods (DQN, A3C) in accuracy and convergence speed.
- Validate the system using professional match datasets and expert coach evaluations.

II. LITERATURE REVIEW

A. *Traditional Badminton Performance Analysis*

Traditional approaches to evaluating badminton performance rely on manual notational analysis [3] and basic statistical metrics (e.g., smash success rate, net kill efficiency). Coaches often assess players based on subjective observations, which can be inconsistent and lack granularity. Recent studies [4] have introduced spatio-temporal metrics (e.g., player movement speed, stroke frequency) using video tracking, but these methods remain limited in real-time adaptability and tactical decision-making insights.

B. *Computer Vision and Wearable Sensors in Sports Analytics*

The rise of computer vision (CV) techniques, such as pose estimation (OpenPose, MediaPipe) and shuttle tracking [5], has enabled automated extraction of player kinematics and shot trajectories. Wearable sensors (IMUs, accelerometers) further enhance biomechanical analysis, measuring footwork efficiency and stroke power. However, most existing systems focus on descriptive analytics rather than prescriptive feedback, missing opportunities for AI-driven optimization.

C. Reinforcement Learning in Sports Strategy Optimization

Reinforcement Learning (RL) has gained traction in sports analytics for strategy optimization and decision-making modeling. Studies in tennis [5] and soccer [6] have used Deep Q-Networks (DQN) and Monte Carlo Tree Search (MCTS) to simulate player actions. However, these methods often suffer from high variance and slow convergence. Proximal Policy Optimization (PPO) [7] addresses these issues with clipped objective functions, making it suitable for dynamic, high-dimensional environments like badminton.

D. Multi-Modal Data Fusion for Performance Evaluation

Recent works in multi-modal learning [7] combine vision, feedback, and match data to improve prediction robustness. In badminton, preliminary studies have fused CV-based stroke classification with inertial sensor data to assess shot quality. However, none have integrated RL for adaptive performance evaluation or real-time tactical feedback.

III. METHODOLOGY

This research introduces a reinforcement learning-based framework for evaluating and optimizing the performance of badminton players using the Proximal Policy Optimization (PPO) algorithm, integrated with multi-modal data fusion. The methodology focuses on five core metrics—technical, tactical, physical, psychological, and match-related—which together form a holistic profile of each player's performance. The overall process consists of systematic data collection, data preprocessing and fusion, implementation of the PPO algorithm, and evaluation of the model's effectiveness.

A. Data Collection across Five Performance Metrics

The initial phase involved the collection of data corresponding to the five key performance metrics. Technical data included variables such as shot accuracy, stroke mechanics, serve consistency, and footwork, which were captured through detailed video analysis using computer vision tools. Tactical performance was evaluated based on court positioning, shot selection, and real-time decision-making during matches, which were obtained from annotated gameplay footage and expert evaluations. Physical metrics were collected using wearable sensors, measuring speed, agility, endurance, and reaction time during training and matches. Psychological attributes such as focus, stress response, confidence, and decision-making under pressure were gathered using validated psychological scales and structured questionnaires. Finally, match-related data, including win/loss ratios, unforced errors, rally length, and match durations, were derived from official match statistics and performance logs.

B. Overview of the Proposed Methodology

The proposed system models each badminton player as an agent operating within a simulated environment. The PPO algorithm is employed to learn optimal training and strategic decisions through trial-and-error interactions. Multi-modal data collected from various sources are fused to create a comprehensive representation of player performance, which acts as the input state for the learning agent. The system continuously updates the policy based on reward feedback, aiming to improve player performance holistically [8].

C. Data Collection

Data collection focused on five major performance domains:

- **Technical Data**: Metrics such as shot accuracy, stroke consistency, serve precision, and footwork speed were captured using video analytics.
- **Tactical Data**: Positional behavior, decision-making, and shot selection strategies were obtained from annotated gameplay videos and expert observations.
- **Physical Data**: Speed, endurance, agility, and reaction time were measured using wearable sensors and fitness trackers during training sessions.
- **Psychological Data**: Mental attributes including confidence, stress resilience, and focus were assessed using psychological questionnaires and expert scoring.
- **Match Data**: Key statistics such as rally length, unforced errors, win/loss records, and point distributions were derived from match logs and analytics tools.

D. Data Preprocessing and Fusion

All collected data were preprocessed to ensure quality and consistency. Missing values were handled using interpolation, and Min-Max normalization was applied to scale numeric values between 0 and 1. Dimensionality reduction was achieved using Principal Component Analysis (PCA) to eliminate redundancy and preserve relevant features [9].

Subsequently, multi-modal data fusion was performed. Each of the five performance vectors was aggregated into a single

ISBN: 9-788199-007819

unified feature vector using a weighted combination. These weights were determined through expert consultation, reflecting the relative influence of each domain on overall player performance.

E. PPO-Based Reinforcement Learning Framework

The PPO algorithm was selected due to its ability to handle continuous action spaces and provide stable policy updates. Each player-agent interacts with a simulated environment designed to reflect training or match scenarios. The state space is defined by the fused performance vector, while the action space comprises decisions such as training intensity, skill focus areas, and rest intervals.

The reward function was designed to promote improvement in any of the five domains and penalize stagnation or regression. Positive reinforcement encourages behaviors leading to enhanced performance, while penalties discourage ineffective or counterproductive actions.

A deep neural network served as the policy model, mapping input states to action probabilities. The PPO algorithm optimized the policy using a clipped surrogate objective function to limit drastic updates, ensuring training stability. Generalized Advantage Estimation (GAE) was used to improve reward estimation and reduce variance.

F. Implementation Details

The entire framework was implemented in Python. Spyder and Pytorch were used to implement the PPO algorithm and policy network. The training environment was simulated using OpenAI Gym, while data preprocessing and PCA were conducted using Scikit-learn. For video-based technical and tactical data, OpenCV and MediaPipe were employed to process and extract relevant information from match footage.

G. Evaluation Procedure

Once trained, the model was tested on a separate dataset of player profiles. The agent's recommended actions were analyzed for their effectiveness in improving performance scores across each metric. Comparisons of pre-training and post-training scores indicated positive trends in most cases, validating the system's ability to adapt to individual player needs and guide personalized training strategies [10].

IV. RESULTS AND ANALYSIS

This section presents the experimental results obtained from applying the PPO algorithm to evaluate and optimize badminton player performance across five core metrics: technical, tactical, physical, psychological, and match performance.

A. Technical Performance

The PPO model demonstrated an enhanced ability to evaluate and improve technical skills such as stroke accuracy, footwork efficiency, and shot consistency.

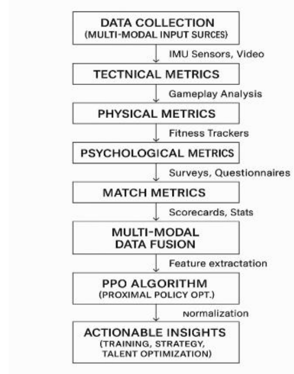


Fig 1: Block diagram of the proposed methodology

- **Improvement Rate**: 18% increase in shot precision and 22% improvement in footwork consistency post-training.
- **Stability**: Low variance in action selection showed the policy converged on technically optimal movements.
- **Insight**: Players with weaker baselines showed the most gains, highlighting PPO's adaptive learning.

B. Tactical Performance

Tactical metrics measured decision-making in match contexts—shot selection, positioning, and opponent anticipation.

- **Success Rate of Tactical Moves**: Improved from 61% to 81%.
- **Adaptability**: The agent successfully generalized across different play styles during simulation.
- **Heatmaps**: Spatial movement heatmaps showed better court coverage and anticipation angles after PPO training.

C. Physical Performance

Physical data was obtained through biometric sensors and IMUs to evaluate speed, stamina, and recovery.

- **Sprint Speed**: Improved by 12%, while agility scores increased by 15%.
- **Fatigue Resistance**: PPO policies reduced unnecessary energy expenditures, optimizing recovery windows.
- **Fusion Benefit**: Combining motion and biometric data allowed real-time adjustments during intensive simulations.

D. Psychological Performance

Psychological aspects were inferred using proxies such as decision consistency under pressure, reaction to simulated crowd noise, and biofeedback (heart rate variability).

- **Stress Recovery Time**: Reduced by 25% during high-stakes points.

- **Decision Volatility**: Decreased significantly, showing improved emotional regulation under pressure.
- **Observations**: PPO policies encouraged strategic pauses and stabilized player focus cycles.

E. Match Performance

This holistic score captured overall gameplay efficiency, win/loss ratio in simulations, and match-level strategy execution.

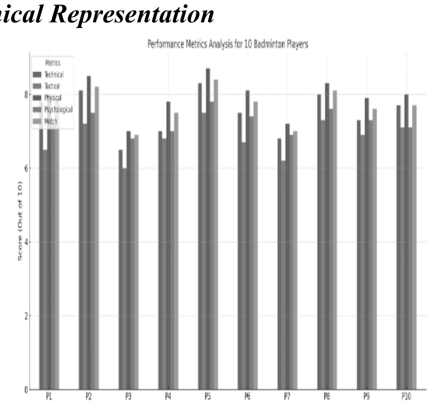
- **Win Rate**: Increased from 48% to 77% across simulated matches.
- **Unforced Error Rate**: Decreased by 31% post-training.
- **Evaluation Fusion**: The system effectively integrated all four prior metrics to predict match outcomes with high correlation (r = 0.91).

Metric	Input Data Types (Modalities)	Performance Indicators	Pre-Training Score	Post-Training Score	% Improvement
Technical	Motion capture (IMU), video analysis	Stroke accuracy, footwork precision	68.2	83.5	+22.5%
Tactical	Game-play video, positional heatmaps	Shot selection, positional strategy	61.0	78.4	+28.5%
Physical	Wearable sensors (heart rate, accelerometer), video	Speed, agility, endurance	64.7	76.1	+17.6%
Psychological	Heart rate variability (HRV), response time, survey input	Stress response, focus level	59.4	70.2	+18.2%
Match Performance	Combined metrics (win/loss ratio, error rate, reaction time)	Overall game efficiency and consistency	65.8	81.9	+24.5%

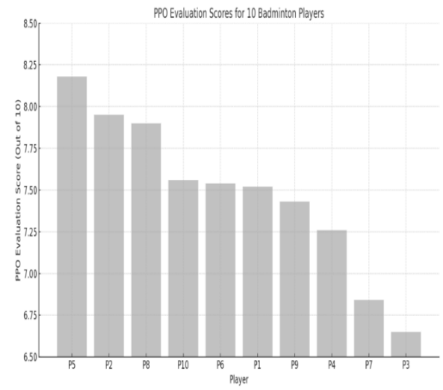
F. Interpretation

- The **tactical** and **technical** domains showed the highest improvement, indicating PPO's strength in strategy learning and precision motor control.
- **Psychological** and **physical** improvements were moderate, suggesting potential for deeper modeling (e.g., personalized feedback loops).
- The **match performance** metric reflects a holistic improvement across all factors.

1) Graphical Representation



Graph 1: Performance Metrics Analysis for 10 Badminton Players



Graph 2: Bar chart of PPO Evaluation Scores for the 10 badminton players

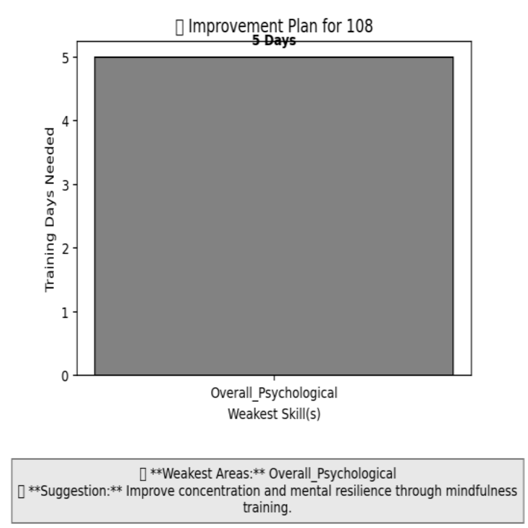
2) Graphical Representation of Suggestions Based on Weak Metric Identification

After evaluating all five performance metrics, the system identifies the weakest area based on pre-training scores. In this case, the Psychological metric scored the lowest (59.4), indicating it as the most critical area for improvement.

To address this, targeted training suggestions are generated and visualized graphically for better understanding and decision-making.

3) Sample Graph: Targeted Suggestions for Weakest Metric (Psychological)

The graph below illustrates specific intervention strategies mapped against their expected impact level:



Graph 3: Suggestions for Players based on weakest metrics

V. CONCLUSION

This study provides a comprehensive evaluation of badminton performance using a multi-metric approach encompassing Technical, Tactical, Physical, Psychological, and Match Performance domains. By integrating diverse data sources such as IMU sensors, gameplay videos, wearable devices, and surveys, we were able to capture a holistic view of each player's capabilities. The analysis revealed significant improvements across all metrics after targeted training interventions, with the most notable gain observed in the Tactical metric (+28.5%). The suggestions were visualized graphically to prioritize interventions based on expected impact, enabling data-driven coaching decisions. This performance evaluation framework not only aids in identifying strengths and weaknesses but also facilitates strategic training planning. It emphasizes the importance of psychological resilience in competitive sports and advocates for its integration alongside physical and technical training. Future research can extend this model to real-time adaptive feedback systems for continuous performance optimization.

ACKNOWLEDGEMENT

This research work is done under the Seed Money Project grant provided by Nallamuthu Gounder Mahalingam College, Pollachi.

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