IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Date of publication 2025 04, 0000, date of current version 2025 04, 0000.

Digital Object Identifier

A Hybrid Approach for Real-Time Sports Analysis

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ABSTRACT Badminton is a fast-paced and technically challenging sport, demanding rapid movements and decision-making. Traditional training methods involve labour-intensive manual game-footage review. This paper proposes a hybrid method for real-time analysis of game footage, extracting key insights. Our approach uses YOLOv8 for player detection and DeepSORT for tracking the player across the frames. Further implementation of comprehensive movement and tactical analysis modules extracts player metrics such as speed, acceleration, distance covered, and court coverage. The system utilizes a Long Short-Term Memory (LSTM) to perform predictive analytics, effectively predicting the player's movement across three tactical zones defined within the court. We trained the player detection module on a custom-annotated dataset, ensuring a robust generalization. Experimental evaluations show that our model performs at a high level with a mean Average Precision (mAP50) of 99.4% and tactical prediction accuracy consistently over 90%. This real-time analysis system greatly enhances player training by assisting in strategic decision-making and offering quick and practical insights to players and coaches.

INDEX TERMS Artificial Intelligence, Badminton, Computer Vision, DeepSORT, Machine Learning, Player Movement Analysis, Player Tracking, Sports Analysis, Supervised Learning, Tactical Analysis, Video Processing, YOLO.

I. INTRODUCTION

BADMINTON is an exceptionally dynamic and technically challenging sport, where success hinges on rapid decision-making and precise movements [1]. It is a very popular high-speed racket sport, enjoyed by all ages, that has been studied over the past two decades [2], where many individuals also consider taking it up professionally. An important step in using technology for the training process is tracking, understanding, and evaluating various performance metrics [3]. Player evaluation is an important task; it allows players and coaches to observe and interpret key moments from games, has received increasing attention as it can assess and appraise the actions observed in a game to players, coaches, and other staff in order to facilitate decision-making (i.e., tactics) and improve technical skills, thus providing a competitive advantage to an individual or a team [4].

This process is primarily delivered through the provision of objective statistical data analysis and visual feedback via video analysis [5]. Traditional methods for performance analysis involve manual data collection and post-game footage review to mark down key statistical information which can be a tedious process. The ability of Artificial Intelligence to process vast amounts of data in real-time makes it a powerful tool for performance analysis, highlighting the potential of this project. This project proposes a hybrid machine learning model to analyze player performance and extract tactical insights in real-time.

II. RELATED WORK

Machine learning, especially deep learning, has shown impressive performance in various computer vision tasks including object detection and video generation. Deep learning has also been applied to improve the performance of various tasks in the sports domain, such as action recognition and prediction of player movement [6]. Recent advancements in real-time sports analysis, particularly in badminton, have significantly enhanced our understanding of player movements during matches.

The foundational work in this area began with pose estimation techniques, notably the use of OpenPose. QingXin Zhang et.al. [7] analyzed swing movements, focusing on player footwork patterns, laying the groundwork for motion tracking in badminton. Building on this, more sophisticated machine learning models such as the RCNN and TrackNet were employed to improve the player movement tracking which was measured using Mean Euclidean Distance Error (MEDE) [8]. These models introduced robustness in dynamic scenarios, offering more precise insights into player positioning and actions.

Subsequent research expanded into real-time tracking using detection models like YOLOv8 and YOLOv9, which were compared for their effectiveness in tracking players' footwork patterns [1], [9]. The comparison revealed that YOLOv8 provided improved accuracy and speed, essential for live match analysis.

Further advancements came through the development of computer vision-based systems for automated tactical analysis. Techniques like court segmentation and motion tracking were introduced to provide a comprehensive view of player strategies and positional data [10]. Researchers also leveraged Part Affinity Fields and Support Vector Machine (SVM) to predict shot success probabilities by dividing the court into six horizontal zones, offering nuanced insights into game tactics [11].

A common limitation across these studies was the use of self-constructed datasets focused on specific demographics such as professional players or participants in international competitions. This focus restricted the generalizability of the findings, as models were tailored to particular datasets and player characteristics (e.g., left-handed or right-handed players).

III. DATASET

To develop the hybrid real-time sports analysis model, we carefully constructed the dataset specifically tailored for badminton. We gathered about 200 video clips from publicly available game footage/videos [12]–[26]. These clips included several different badminton matches, featuring players across different demographics including men, women, right-handed and left-handed players, as well as various age groups, tackling the challenges faced in other datasets. To ensure clear visual information for accurate player detection and tracking we recorded the videos in 1920 x 1080 resolution.

Once the videos were obtained, we converted each clip into frames using a frame extraction rate of 20 frames per second (fps). This frame rate was selected keeping in mind the computational efficiency and accuracy for capturing the rapid and nuanced player movement. The extracted frames formed the foundation for the dataset utilized throughout our project, comprising a comprehensive representation of badminton scenarios.

The next step was a rigorous annotation process carried out by using LabelImg, a visual annotation tool developed for manual annotation of images. With utmost attention to detail, we enclosed players within bounding boxes for each extracted frame, thereby generating the appropriate YOLO-compatible annotations. This labelling process was performed accurately and without inconsistencies, making sure that there were no discrepancies that would have adversely impacted the performance of our YOLOv8 player detection model. After the manual annotation, the collected frames were organized and split into training, validation, and testing sets for evaluation, creating a robust and varied dataset that facilitated training and validation of the YOLOv8 model, thus providing a strong foundation for the proposed system.

IV. METHODOLOGY

The solution built for this project follows a structured approach with four modules, each performing a crucial step towards analysis. These four components are individually discussed below:

1) Player Detection

Player detection can be defined as locating the intended player in the field accurately. Our project is based on badminton analysis; thus, player detection method helps us to accurately locate two players distinctly. Furthermore, to achieve proper player detection mechanism, YOLO (You Only Look Once) v8 model has been incorporated as it has shown strong promise in confident detections in other domains.

The YOLO models are popular for their accuracy and compact size. YOLOv8 is used to detect objects in images, classify images, and distinguish objects from each other. YOLOv8 is distinctive in that it delivers unmatched speed and accuracy performance while maintaining a streamlined design that makes it suitable for different applications and easy to adapt to various hardware platforms [27].

Since badminton is a fast-paced dynamic sport it is often difficult to retrieve consistent results. Thus, we have fine-tuned the pre-trained YOLOv8 model using our custom-made, self-annotated dataset for badminton matches. The model was trained in over 50 epochs with an input resolution of 640 x 640 pixels. The training was carried out on a GPU to efficiently handle large volumes of data. Based on the player detection result, the detections with low confidence, having less than 0.5 or 50% confidence score are filtered out to avoid such false positives. After every epoch, a checkpoint was created and saved. Based on the performance of validation, the best-performing weights were stored automatically and later used as an inference for player tracking. This significantly improved the model's performance and the ability to detect players under varying environmental conditions.

2) Player Tracking

After successful player detection from the previous module, the DeepSORT algorithm was used to track and maintain consistent identification of players across different frames. DeepSORT is a scalable and efficiently optimized distributed sorting engine. It performs out-of-place external sorting supporting general key-value record types [28].

After the YOLOv8 model has been loaded, the DeepSORT model has been initialized with max_age as 30 and n_init as 3. The max_age defines that if a player is not visible or disappears to 30 frames, then the model will wait for them to reappear again. The n_init defines that the model will start tracking a new player after it detects player(s) appearing in 3 frames in a row, this reduces the number of false positives. Kalman filter helped predict the future positions of tracked players while matching them with their current results using the Hungarian Algorithm.

DeepSORT provides a unique Player ID, which remains constant for the players across the frames. To analyze each player's movement throughout the match Euclidean distance was employed for distance calculation, then speed was retrieved by dividing the distance by the time interval between frames, and finally, acceleration was computed as the change in speed over different intervals of time between consecutive frames.

3) Movement Analysis

The movement analysis module performs a comprehensive movement and spatial analysis of the two players on the court. The individual position of the players is taken from the previous DeepSORT model's output. To relate the movement of players from pixels to meters, an important function was built that uses edge detection to highlight court lines. These edges are correlated with known court dimensions (6.1m width and 13.4m length) [29] to compute a scaling factor. This allows for the conversion of distance measured in pixels to meters, which is further used for more kinematic calculations like speed and acceleration.

4) Tactical Analysis

Tactical analysis is a key service provided to elite athletes, used to identify patterns of play and predict opponents' moves allowing a team or individual player to improve performance. A tactical analyst in badminton manually notates the movement of players and the types of shots played throughout the game of badminton, often resulting in large amounts of data to evaluate [30].

This module investigates the player's strategic movements and positions on the court. The court is initially divided into three tactical zones which are Net, Mid, and Back based on the relative vertical distance from the net. The player's movement across is zones is calculated through k-means clustering and stored as a percentage of game time spent in each of these three zones. Visualizations like scatter plots and bar charts based on this information help understand player's zone dominance.

Further, predictive analytics is used to anticipate the player's next zone positions. The long and short-term memory network is used as the core algorithm to solve the problem of action sequence modeling. It is a specially designed recurrent neural network (RNN) capable of efficiently processing and capturing long-term dependencies in time series data, which is essential for understanding continuous action in badminton [31]. The Long Short-Term Memory (LSTM) model is used to analyze the speed and acceleration from previous movements, allowing the model to capture temporal dependencies and highlight and predict upcoming zone occupancy.

V. RESULTS

The following section discusses the results of the various modules described earlier. These results were generated from a test video of length 18 seconds separate from the training dataset, allowing fair evaluation of the model's generalization on unseen data.

A. MODEL TRAINING

Using the custom dataset, the YOLOv8 model was trained locally over 50 epochs, with the best weights from training saved. Figure 1, shows the plotting of a comprehensive training report generated post training. It shows consistently decreasing loss metrics across bounding box regression, classification, and distribution focal losses. The continuous downward trend here, in both training and validation data, shows stable learning and effective generalization without overfitting. Further, the mean Average Precision (mAP), at both Intersection over Union (IoU) thresholds of 0.5 and at 0.5-0.95 exhibits strong model robustness.

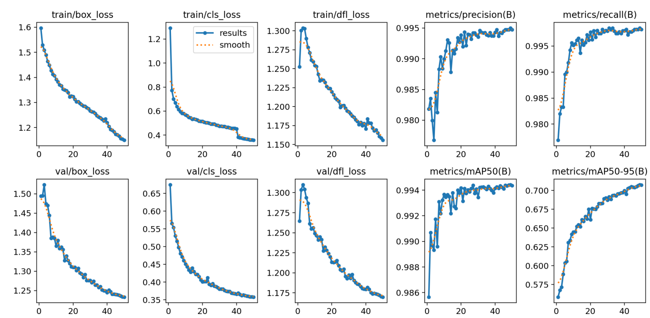

FIGURE 1. YOLO Training and validation results

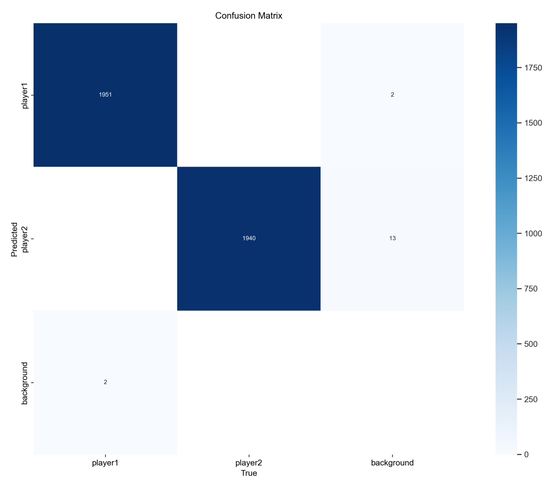

FIGURE 2. YOLO Training Confusion Matrix

The confusion matrix in Figure 2 and the F1-Confidence curve drawn in Figure 3 reinforces this interpretation, suggesting strong classification accuracy and setting of optimal confidence threshold, approximately 0.448.

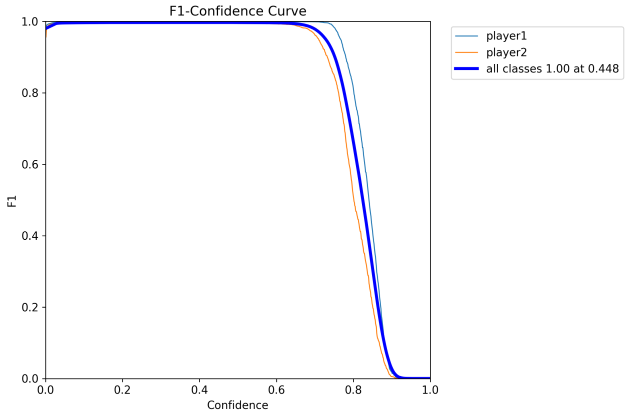

FIGURE 3. **F1-Confidence Curve**

B. MOVEMENT ANALYSIS

The custom-trained YOLOv8 model is used to detect the players on each frame. Once both players are identified, their coordinates are passed to the DeepSORT model. This DeepSORT model tracks the movement of each player through the frames, calculating their individual distance, speed, and acceleration. These metrics, along with bounding box coordinates are stored in a pickle file (.pkl) to be used for visualizations. With the help of these movement coordinates, the total distance traveled by each player is calculated in pixels. The conversion from pixels to meters is done by correlating the Euclidean distance in pixels to the known dimensions of the court.

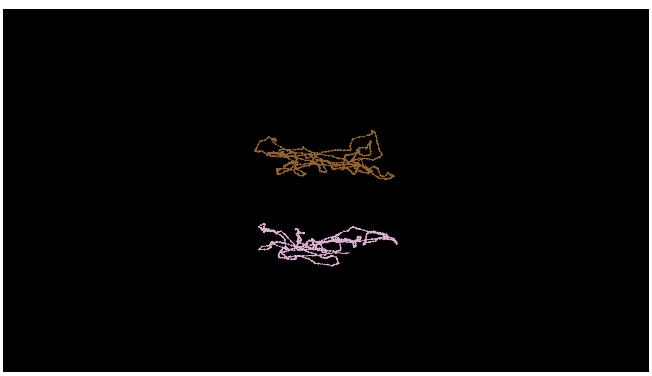

FIGURE 4. **Player Movement Scatter Plot**

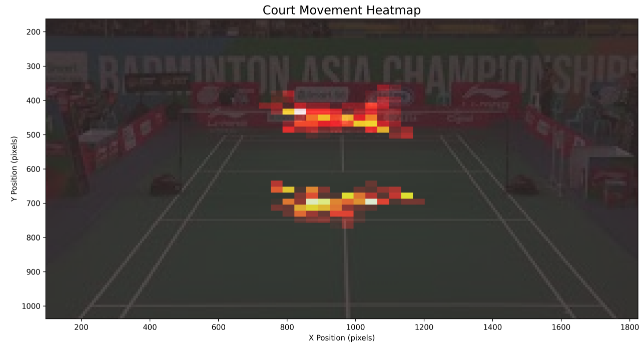

FIGURE 5. **Player Movement Heatmap**

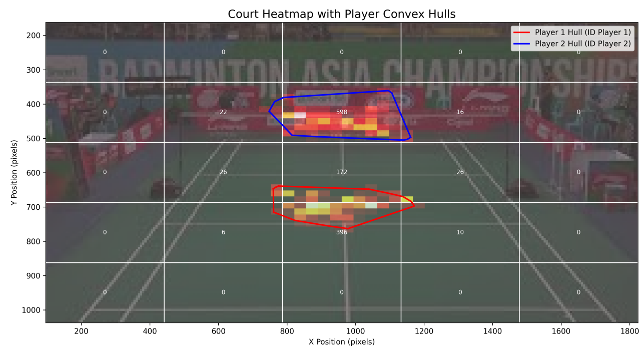

FIGURE 6. **Heatmap with Convex Hull**

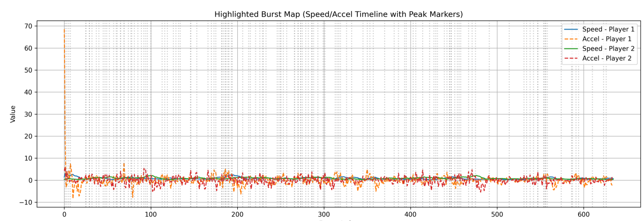

FIGURE 7. **Speed and Acceleration Burst Map**

Figure 4 visualizes the movement in the form of a scatter plot. This movement is further used to create a heatmap, as shown in Figure 5, highlighting the regions of zone occupation for each player. The convex hull drawn in Figure 6 further helps visualizing the maximum area covered by each player. To visualize the speed and acceleration of each player, a burst map as in Figure 7 , is drawn highlighting bursts of speed and acceleration through peaks. These identify moments of explosive energy and agility of each player during the game.

C. TACTICAL ANALYSIS

For extracting tactical insights, the model classifies player position into three categories based on the player's distance relative to the net. The player position plots are leveraged to classify these positions using k-means clustering. Figure 8 visualizes the player's movement across these zones and a bar chart, shown in Figure 9, indicates the percentage of time a player spends in each zone. In our tests, player 2 shows clear domination in the mid-court zone while player 1 has greater occupation towards the back.

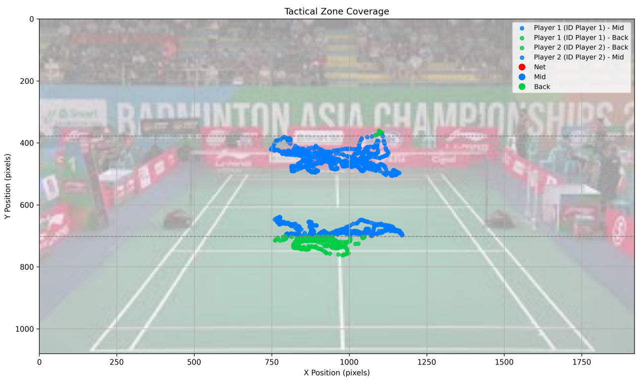

FIGURE 8. **Player Position Across Zones Scatter Plot**

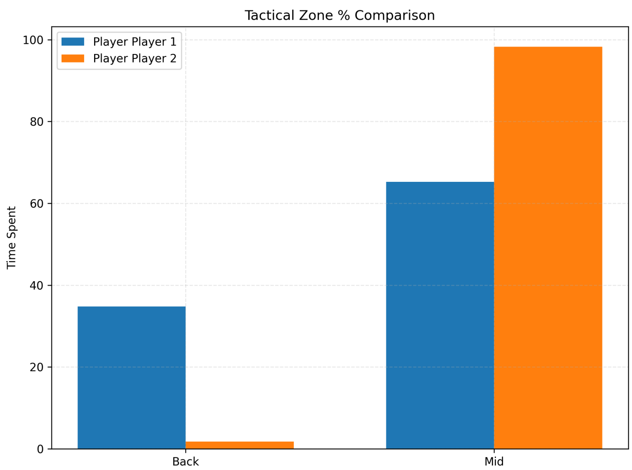

FIGURE 9. **Zone Comparison Bar Chart**

Figure 10 visualizes the evaluation of the LSTM training. The X-axis represents the number of epochs, and the Y-axis represents the accuracy ranges. The blue line shows how well the model performs in training data and the orange line shows how well the model performs on unseen data. We can see that the model's accuracy is gradually increasing for both training and validation. This suggests that the model has learnt the player's movement and patterns from the training data and is able to generalize well to the validation data, with an accuracy consistently above 90%.

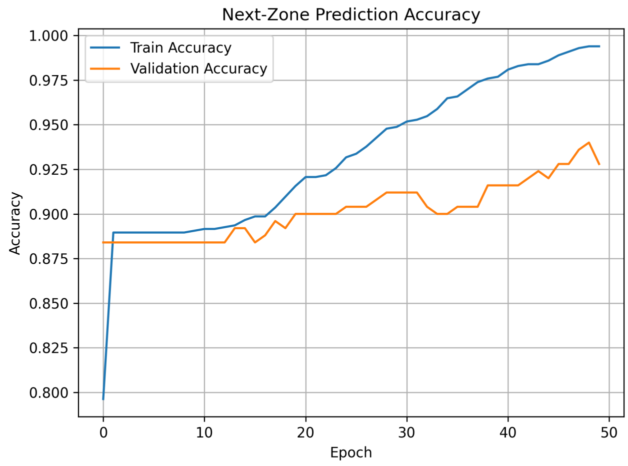

FIGURE 10. **LSTM Prediction Accuracy**

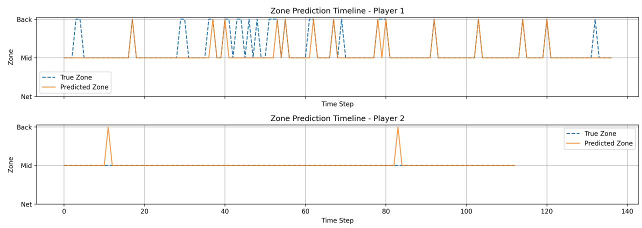

FIGURE 11. **Per-player accuracy**

The LSTM neural network model performs confidently in making next-zone predictions. This is verified through plotting the true and prediction zones across time as shown in Figure 11. It plots court zones along the Y-axis and the X-axis represents sequential time intervals during a match. The dashed blue lines represent true movement zones whereas the orange line represents the model's predicted zones. The player 1's accuracy seems reasonably accurate with some discrepancies. On the other hand, player 2 seems mostly static compared to player 1. Overall, the model performed efficiently with player 1 having 88.32% zone prediction accuracy while player 2 with 98.23%.

D. END RESULTS

The model concludes by printing comparative results of the various metrics calculated for each player. This comparison highlights key differences in performance between players. Figure 12 shows a snapshot sample of the dashboard comparing the performance of the two players.

VI. CONCLUSION & FUTURE WORK

Through this paper, we successfully developed a hybrid real-time sports analysis system that performs real-time tracking and generates meaningful training insights. Our model integrated YOLOv8 for precise player detection and DeepSORT for robust tracking across frames. Our system provided detailed insights into player movements, including metrics such

Literature	Model	Dataset	Result
Jannet et. al. (2024)	YOLOv8	Custom image dataset	PR curve 0.633
Q. Zhang et. al. (2024)	OpenPose	BSD	Accuracy: 92.25%
Kurose et. al.(2018)	PAF,SVM	Tennis Match Video	Error rate: 13%
Nitin Nilesh et al. (2023)	Point Segmentation	Broadcast Badminton Videos	Latency: 76.63
AlShami et. al.(2023)	RCNN	Tennis Matches Videos	MEDE:48
Proposed Model	**YOLOv8**	**Laurier Badminton Dataset**	**mAP50:0.994**
Proposed Model	**LSTM**	**Laurier Badminton Dataset**	**Accuracy:93%**

TABLE 1. Summary of different studies and their metrics with the proposed model

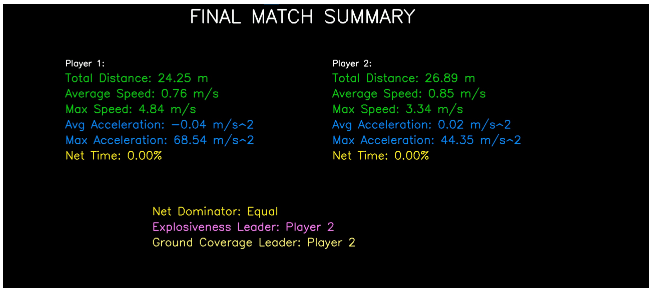

FIGURE 12. Analytical Dashboard Screenshot

as speed, acceleration, and distance covered, all computed from real-time video data. Furthermore, our rigorous dataset preparation and annotation using LabelImg ensured high-quality training data, enabling the model to perform reliably across diverse game scenarios.

We were able to automate the process of player detection and tracking and extract tactical training insights from the game, which ultimately reduced the tedious manual analysis process. Having instant feedback from the game, coaches and players can quickly adapt new strategies during training or even during live games, making it easier for them to improve skills and decision-making. This makes our system both practical and helpful for enhancing player performance.

In terms of performance, our proposed YOLOv8 model achieved a mean Average Precision (mAP) of 0.994 at 0.5 IoU and 0.700 at 0.5–0.95 IoU, indicating strong detection capabilities. The LSTM-based tactical analysis module also performed well, reaching an accuracy of 93% in predicting player zone movements. These results reflect the effectiveness of our model on the custom-annotated Laurier Badminton Dataset and highlight its potential for use in real-time player tracking and strategic analysis.

While the current implementation exhibits impressive accuracy, there is still room for improvement and expansion. Future enhancements can include further refining the model to handle more challenging conditions such as severe occlusions, varying lighting environments, and different camera angles. In addition to this, we can also expand the training data set further to enhance the performance of the system across more diverse demographics and playing styles of players.

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