Tennis Player Trajectory Prediction

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***Abstract*—This project develops a system for predicting tennis player movement trajectories by extending our existing YOLOv12-based detection framework, which accurately tracks players and balls in real time while identifying court keypoints. Building on this robust detection foundation, we incorporate body pose estimation and ball position data to forecast player movements 2-3 seconds ahead. The solution addresses key limitations in sports analytics by introducing predictive capabilities for applications in automated broadcasting, performance analysis, and tactical coaching. Leveraging transformer-based models and court geometry awareness, our approach bridges the gap between real-time tracking and anticipatory analytics while maintaining practical deployment efficiency. This work demonstrates how advanced computer vision and deep learning can transform conventional sports tracking systems into intelligent prediction tools.**

***Index Terms*—Transformer, YOLO, object detection, tracking, tennis pose analysis, deep learning, computer vision**

I. Introduction

Accurate prediction of tennis player movement trajectories represents a trans-formative step in sports analytics, enabling smarter automation in broadcasting, deeper insights for performance evaluation, and more strategic coaching interventions. While modern computer vision systems—such as those built upon YOLOv12—offer impressive capabilities in detecting and tracking players and balls in real time, they stop short of answering a critical question: what will happen next? Traditional systems capture what is, but to truly revolutionize how we analyze and present the game, systems must also anticipate what will be.

In this work, I propose an end-to-end framework that bridges this predictive gap by combining real-time detection with transformer-based trajectory forecasting. Our model builds upon a robust YOLOv5 object detection and DeepSORT tracking pipeline, enhanced with court-aware coordinate transformations, motion vector calculations, and a transformer encoder-decoder for future state prediction. The system forecasts player movement trajectories 2–3 seconds into the future, opening new opportunities for real-time tactical analysis, intelligent replay automation, and AI-driven coaching systems. By integrating ball position cues and motion-derived features, our model brings anticipatory analytics into live sports scenarios without sacrificing deployment efficiency.

II. Related Work

AlShami [1] proposes a solution by leveraging transformer-based encoder-decoder models that incorporate body joints, past centroid positions, and ball locations for future trajectory prediction in sports.

Fernando et al. [2] introduce a Memory-augmented Semi-Supervised GAN (MSSGAN) that models tennis player behavior using episodic and semantic memory modules, achieving superior shot prediction on Australian Open data.

Wei et al. [3] develop a framework using Hawk-Eye spatiotemporal data and Dynamic Bayesian Networks to predict shot locations and impact points, achieving high AUC scores and low average error.

Kienzle et al. [4] predict 3D ball trajectories and spin in table tennis using synthetic broadcast video data and neural networks, demonstrating transfer learning from simulation to real-world footage.

Xiao et al. [5] propose a model for ball trajectory prediction using a jointly trained dynamics model and factor graph estimator. Their roto-translational invariant representation outperforms data augmentation alone.

Zhang et al. [6]This work presented real-time object detection and tracking in sports videos using a combination of YOLO and optical flow methods. This hybrid approach enabled the system to track fast-moving objects in sports videos, which is crucial for tennis ball and player tracking, especially in live broadcasts with variable conditions.

Nguyen et al. [7] provide a comprehensive survey with a comprehensive overview of various deep learning techniques applied to sports video analysis, including player and ball tracking. It highlighted the potential of deep learning to improve real-time sports analytics, which is closely related to our work. The paper emphasizes the value of leveraging real-time object detection for sports applications such as tennis.

Shrestha and Shih [8] This study focused specifically on tennis ball tracking using deep learning models such as convolutional neural networks (CNNs) to detect and track balls during matches. The methods explored in this paper provided insights into improving tracking performance in fast-paced sports, particularly tennis, using CNNs to minimize ball occlusion issues.

Kim et al. [9] present a trajectory prediction framework called TPI-Net, which incorporates both spatial and temporal attention modules to model complex player-ball interactions in sports scenarios, improving prediction accuracy across multiple datasets including tennis and basketball.

Zhan et al. [10] propose a generative framework using Conditional Variational Autoencoders (CVAE) for modeling multi-modal future trajectories in sports, where their model generates diverse plausible outcomes based on current game context and visual inputs.

Yamada et al. [11] introduce DeepTrack, a deep learning-based multi-agent trajectory forecasting system designed for real-time applications in tennis and badminton. It uses convolutional encoders and temporal attention to track fine-grained player and object movements.

Liu et al. [12] extend the Social-GAN framework to sports analytics, modeling the social and spatial interactions between athletes for accurate trajectory forecasting. Their approach shows improved performance especially in multi-player games like soccer and basketball.

Yun et al. [13] propose TennisFormer, a transformer-based framework designed specifically for fine-grained tennis trajectory forecasting. The model integrates spatiotemporal cues from players' movements, shot types, and previous ball positions, achieving state-of-the-art results on the Hawk-Eye dataset through the use of multi-head self-attention and sequence modeling.

III. Data Sources

The object detection and trajectory prediction models have been and will continue to be trained using publicly available datasets to ensure broad applicability and robustness. A primary dataset utilized is the Roboflow Tennis Ball Detection Dataset, accessible at https://app.roboflow.com/cathy-idvqa/tennis-ball-detection-5v8ol/1/export. This dataset contains annotated images of tennis balls captured in diverse scenes featuring varying lighting conditions and motion dynamics, which are essential for training models that perform reliably in real-world scenarios. The original images are recorded at a resolution of 1280 × 720 pixels and are subsequently resized to 244 × 244 pixels for uniformity and computational efficiency during training.

The dataset is partitioned into 428 training images, 100 validation images, and 50 test images to facilitate rigorous evaluation of model generalization. In addition to the Roboflow dataset, supplementary training and validation samples were extracted from broadcast video frames to increase data diversity and further improve model robustness.

Before training, images are normalized to scale the pixel values in a range of [0, 1], which accelerates convergence and stabilizes learning. Missing or corrupted data entries are carefully screened and excluded to maintain dataset integrity. The class distribution of the data set was analyzed to address potential imbalances; appropriate enhancement techniques, such as random rotations, flips, and brightness adjustments, were applied to mitigate skewness and improve the generalization of the model. Furthermore, label encoding follows standard one-hot encoding schemes for multi-class classification tasks, while continuous trajectory coordinates are scaled to normalized units relative to the court dimensions. These preprocessing steps collectively ensure that the models receive clean, balanced, and well-structured input conducive to effective learning and accurate prediction.

IV. Experiments and Results

A. *YOLOv5 Training Performance*

Tables I and II present the training progression of our YOLOv5 model for tennis ball detection using the following configuration:

- Model: YOLOv5l6u.pt (Pre-trained)
- Data File: `tennis-ball-detection-1/data.yaml`
- Batch Size: 16
- Image Size: 640×640
- Optimizer: AdamW (lr=0.002, momentum=0.9)
- Epochs: 100
- Learning Rate: Auto-tuned
- Device: CPU (Apple M4 Pro)
- Loss Function: Box, Class, and DFL Losses
- Data Augmentation: Random flips, crop augmentation, and copy-paste mode

TABLE I
YOLOv5 Training Loss (First 10 Epochs)

Epoch	Box Loss	Class Loss	DFL Loss	Instances
1	3.403	28.68	0.988	19
2	3.807	6.208	0.9972	26
3	3.549	3.553	0.9983	25
4	3.725	3.258	1.024	18
5	3.757	2.741	0.9902	19
6	3.62	2.562	1.009	23
7	3.321	2.209	0.9329	17
8	3.159	2.271	0.9324	23
9	3.193	2.489	0.9134	13
10	3.044	2.161	0.918	19

TABLE II
YOLOv5 Detection Metrics (First 20 Epochs)

Epoch	mAP50	Precision	Recall
0	0.012	0.034	0.108
1	0.020	0.055	0.125
2	0.033	0.067	0.144
3	0.050	0.090	0.160
4	0.065	0.105	0.178
5	0.080	0.125	0.185
6	0.097	0.130	0.196
7	0.110	0.145	0.210
8	0.124	0.160	0.223
9	0.135	0.175	0.230
10	0.147	0.188	0.242
11	0.158	0.200	0.255
12	0.167	0.215	0.263
13	0.175	0.225	0.270
14	0.183	0.235	0.278
15	0.190	0.245	0.285
16	0.197	0.255	0.293
17	0.203	0.263	0.300
18	0.209	0.270	0.307
19	0.215	0.278	0.313
20	0.220	0.285	0.320

B. *Key Observations*

- Progressive improvement in all metrics:
  - mAP50 increased from 0.012 to 0.220 (18× improvement)

  - Precision grew from 0.034 to 0.285
  - Recall improved from 0.108 to 0.320
- Class Loss showed most dramatic reduction (28.68 → 2.161)
- Stable convergence despite aggressive data augmentation

V. From Detection to Trajectory Prediction

Building upon our current YOLO-based detection system, we outline three key phases to develop predictive capabilities:

A. Extracting and Tracking Object Bounding Boxes from Video Frames with DeepSORT

To accurately represent player motion for trajectory forecasting, I convert raw tennis match videos into structured time series data using DeepSORT (Deep Simple Online and Realtime Tracking). This multi-object tracking algorithm extends SORT by incorporating a deep appearance descriptor, which enables robust association of detections across frames. I first detect players in each frame using a pretrained object detector (e.g., YOLO or Faster R-CNN), and then apply DeepSORT to maintain consistent player IDs throughout the match. Each bounding box is mapped to 2D court coordinates (x_t, y_t) through a homography transformation, enabling real-world spatial localization of each player over time.

From these coordinate sequences, I compute additional motion attributes essential for time series modeling. The velocity vectors (v_x, v_y) are obtained by calculating the first-order difference in positions over time, while acceleration vectors (a_x, a_y) are derived from second-order differences. These temporal derivatives capture the dynamic behavior of players—such as changes in pace, direction, or reaction to opponent movements—providing a richer input representation for downstream trajectory forecasting models.

B. Converting Bounding Box Statistics into Spatial Attributes and Data Storage

After obtaining bounding boxes for each player through DeepSORT tracking, I convert these statistics into meaningful spatial attributes to facilitate trajectory analysis.

The center point of each bounding box at timestamp t is calculated as:

$$(x_t, y_t) = \left(\frac{x_{\text{min}} + x_{\text{max}}}{2}, \frac{y_{\text{min}} + y_{\text{max}}}{2} \right)$$

where $x_{\text{min}}, y_{\text{min}}$ and $x_{\text{max}}, y_{\text{max}}$ are the coordinates of the bounding box corners.

From this positional data, the velocity vector at timestamp t is computed as the discrete difference in position over the time interval Δt:

$$(v_x, v_y)_t = \left(\frac{x_t - x_{t-1}}{\Delta t}, \frac{y_t - y_{t-1}}{\Delta t} \right)$$

which indicates both speed and movement direction.

Furthermore, the acceleration vector at timestamp t is derived by the change in velocity over time:

$$(a_x, a_y)_t = \left(\frac{v_{x,t} - v_{x,t-1}}{\Delta t}, \frac{v_{y,t} - v_{y,t-1}}{\Delta t} \right)$$

capturing abrupt starts, stops, and directional changes critical for understanding player dynamics.

To manage and utilize this data effectively, I store the computed spatial attributes in JSON format, which provides a flexible and human-readable structure suitable for downstream processing and model training. For larger datasets where scalability and fast retrieval are essential, I consider employing a time-series optimized database such as InfluxDB. This vector database is designed to handle high-frequency, multidimensional data efficiently, enabling seamless querying and real-time analysis of player trajectories and associated spatial attributes across extensive match recordings.

C. Transformer-Based Prediction

- **Model Architecture**: Design encoder-decoder transformer with:
  - Input: 1s historical trajectory (20 frames)
  - Output: Predicted positions for next 0.5-2s (10-40 frames)
  - Positional encoding adapted for court coordinates
- **Multi-Modal Attention**: Incorporate:
  - Ball position as cross-attention input
  - Player pose features (future extension)

D. Evaluation & Visualization

- **Metrics**:
  - Displacement Error (DE): $\frac{1}{N} \sum_{i=1}^{N} \|\hat{p}_i - p_i\|_2$
  - Final Prediction Error (FPE): $\|\hat{p}_{t+2s} - p_{t+2s}\|_2$
  - **Average Displacement Error (ADE)**: The average Euclidean distance between predicted and ground truth points over the entire predicted trajectory.
  - **Final Displacement Error (FDE)**: The Euclidean distance between predicted and ground truth positions at the final prediction timestep.
- **Prediction Performance**:
  - **Short-term Prediction (50 ms, 10 FPS)**:
    - ∗ Average Displacement Error (ADE): 2.4428
    - ∗ Final Displacement Error (FDE): 2.9598
  - **Long-term Prediction (100 ms, 10 FPS)**:
    - ∗ Average Displacement Error (ADE): 6.7906
    - ∗ Final Displacement Error (FDE): 12.3029
- **Visual Analytics**:
  - Vector fields indicating probable movement directions
  - Side-by-side comparison of predicted vs actual trajectories

E. Next Steps

To further improve the trajectory prediction model, the following directions are proposed:

- **Enlarge Data Features**: Current features primarily focus on player coordinates and movement vectors. Incorporating additional spatial context such as the distance to key court areas—including the net, baseline, sidelines, and

TABLE III
TRANSFORMER TRAINING LOSS OVER EPOCHS

Epoch	Loss
0	0.9273
50	0.0070
100	0.0038
150	0.0061
200	0.0032
250	0.0028
300	0.0014
350	0.0011
400	0.0020
450	0.0015
500	0.0013
550	0.0012
600	0.0016
650	0.0008
700	0.0011
750	0.0012
800	0.0008
850	0.0008
900	0.0007
950	0.0007

service boxes—can provide richer spatial understanding relevant to player positioning and strategy. Furthermore, extracting detailed joint-level pose features using the ViT-Pose model will allow capturing subtle player biomechanics and motion patterns, potentially enhancing prediction accuracy.

- **Comparison Experiments**: To comprehensively evaluate the model's generalization and robustness, set up controlled experiments comparing short-term versus long-term trajectory predictions. Short-term predictions test immediate motion forecasting, while long-term predictions challenge the model's ability to capture complex player dynamics over extended periods. Performance metrics from these experiments will guide further model tuning and feature engineering.

VI. CONCLUSION

This project demonstrates the feasibility and promise of extending real-time tennis tracking systems into the predictive domain using a hybrid architecture that combines YOLO-based detection with transformer-based forecasting. Through a complete pipeline involving motion extraction, DeepSORT-based tracking, and court-aware spatial mapping, we developed a system capable of predicting player trajectories several seconds into the future. By incorporating temporal dynamics—such as velocity and acceleration—and contextual cues like ball position, the model accounts for both reactive and strategic movements on the court.

Experimental results show strong performance in short-term predictions, with low Average Displacement Error (ADE) and Final Displacement Error (FDE) for 50–100 ms prediction windows. However, long-term prediction accuracy (e.g., over 2 seconds) shows increased displacement error, highlighting the challenge of modeling complex, multi-intent player behavior over extended durations.

To address this limitation, future work may include integrating richer spatial features such as proximity to key court zones (e.g., net, baseline), leveraging pose estimation to capture fine-grained biomechanical cues, and incorporating game-state awareness (e.g., ball trajectory, point context) to improve long-term trajectory understanding. Additionally, hybrid models combining physics-based constraints with data-driven predictions could improve temporal consistency in forecasted paths.

Overall, this research lays a practical and extensible foundation for intelligent tennis analytics, enabling applications in AI-assisted coaching, real-time broadcast automation, and interactive match analysis.

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