TennisIQ: A Deep Learning and Computer Vision-Based System for Automated Tennis Performance Analysis and Coaching

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***Abstract*—This paper introduces TennisIQ, an AI-driven system for intelligent tennis performance analytics and coaching. It integrates deep learning, computer vision, and probabilistic modeling to automatically evaluate player performance from standard match videos. TennisIQ automatically detects and classifies shots into serve, forehand, backhand, volley, and drop shot, while computing shot quality scores based on relevant physical and tactical parameters, and eventually providing AI-based recommendations on shot selection by win probability estimation. The platform provides interactive visualizations of the strong and weak points of players, as well as their improvement trends. Experimental results reveal shot detection accuracy of 96%, classification precision of 93%, and a 20% enhancement in player efficiency. TennisIQ democratizes data-driven tennis coaching by bridging the gap in analytics between professionals and amateurs. Potential extensions include real-time tactical prediction and integration with wearable biomechanical sensors.**

***Index Terms*—Tennis Analytics,Shot Quality Estimation, Artificial Intelligence, Computer Vision, Deep Learning, Sports Performance Analysis, AI Coaching**

I. Introduction

"Tennis, being among the most dynamic and technologically demanding racket sports, necessitates detailed analysis of the players' movements in concert with strategic decision-making. The use of data-driven technologies in recent years has become key to evaluating performances and informing coaching decisions. The fusion of AI and computer vision into sports analytics has opened up new opportunities for the real-time, objective assessment of player technique and match strategy.

A. Background and Motivation

Conventional tennis performance analysis is labor-intensive and erratic since it mainly depends on subjective assessment and manual observation. There is an increasing chance to use video-based analytics to automate this process thanks to developments in computer vision and artificial intelligence (AI). However, most players cannot afford or access the current professional systems, such as Hawk-Eye. The need to make sophisticated tennis analytics accessible and reasonably priced using regular match footage is what inspired TennisIQ. The system offers data-driven insights into player performance by fusing AI-based shot evaluation, trajectory tracking, and deep learning. The objective is to bridge the gap between professional and amateur analysis by assisting coaches and players in objectively identifying their strengths, weaknesses, and best practices.

B. Problem Statement

Conventional approaches to tennis analysis are based on subjective expert judgment and/or manually performed review work, which is time-consuming, error-prone, and lacks quantitative accuracy. Current automated systems are out of reach for regular players as they often depend on expensive hardware, such as motion sensors or high-speed tracking cameras. The problem it tries to solve is the lack of an AI-driven, reasonably priced solution that can reliably analyze tennis performance from regular video footage. TennisIQ attempts to develop a system that can automatically identify shots, classify them, and provide an analysis with real-time insight and AI-based strategy recommendations for enhancing the performance of players.

C. Project Objectives

Tennis IQ's main goal is to create an intelligent artificial intelligence (AI)-based tennis performance analysis system that can use standard match videos to automatically assess player performance. To identify players and the ball, categorize different kinds of shots, and calculate quality scores for serves, forehands, backhands, volleys, and drop shots, the system makes use of deep learning and computer vision algorithms. By utilizing these technologies, Tennis IQ makes professional-level insights available to all players, doing away with the need for costly motion tracking equipment and manual analysis. Furthermore, the project also aims at providing real-time strategic support through visual analytics and AI-generated shot recommendations. Additionally, players can grade their shots, record customized feedback, and track their progress over time. TennisIQ fuses accurate analytics with intuitive visualization tools, inspiring a data-driven yet approachable method of coaching in tennis.

D. Scope of the Research

The goal of this research is to develop and put into use an artificial intelligence (AI)-based tennis performance analysis system that can assess player performance straight from regular match footage. The system's main goal is to use computer vision and deep learning techniques to automate shot detection, classification, and quality scoring. Additionally, it has visual analytics and AI-based shot recommendations to help players understand their tactical efficiency, strengths, and shortcomings. While primarily developed for tennis, the framework can be extended to other racket sports, making TennisIQ a scalable and versatile solution for performance analysis and intelligent sportscoaching.

II. LITERATURE REVIEW

A. Computer Vision in Sports Analytics

Computer vision has been widely used in sports analytics in recent years for trajectory estimation and motion detection. According to R. Smith (2023), algorithms like Kalman Filters and YOLO (You Only Look Once) can accurately and efficiently track fast-moving objects like tennis balls. These technologies have been widely used to identify important match events, predict ball movement, and detect players. But because most systems are made for professional competitions and demand top-notch video feeds, they are not widely available. By applying comparable vision-based tracking methods to regular camera footage, TennisIQ expands on this framework.

B. Deep Learning for Shot Classification

Sports activities and intricate human motions can be effectively classified using deep learning models, particularly Convolutional Neural Networks (CNNs). A CNN-based framework was created by A. Gupta et al. (2022) to accurately classify tennis shots like serves, backhands, and forehands. In order to capture temporal dependencies in player movement, other works combined CNNs with Recurrent Neural Networks (RNNs). Despite these developments, the majority of systems still require a lot of labeled data or are computationally demanding. Using lightweight CNN architectures tuned for quicker inference on actual match footage, TennisIQ overcomes this constraint.

C. Trajectory Estimation and Motion Prediction

For trajectory estimation in dynamic environments, L. Chen (2021) investigated Kalman Filters and Optical Flow algorithms. When the tennis ball is momentarily obscured by players or nets, these models are especially helpful for tracking it. To increase tracking stability, these filters were combined with predictive motion models in later research. Building on these strategies, TennisIQ incorporates Kalman filtering based on FilterPy to preserve fluid and consistent trajectory predictions even under difficult visual circumstances.

D. AI Coaching and Performance Analytics

Tools for performance analysis powered by AI have become essential tools for contemporary sports coaching. AI-based recommendation systems are used by a number of platforms to evaluate player tactics, forecast game results, and provide gameplay commentary. Despite their effectiveness, the majority of current systems concentrate on elite-level performance and depend on expensive infrastructure or proprietary datasets. Using regular match videos, TennisIQ presents a more approachable AI coaching model that provides everyday players with comprehensive performance feedback, shot scoring, and improvement recommendations.

E. Research Gap and Positioning of TennisIQ

Even though sports video analysis has been extensively studied, current tennis systems either rely on expensive gear or don't provide thorough AI-driven feedback. The majority of earlier research focuses on discrete tasks, like trajectory tracking or shot recognition, without incorporating them into a comprehensive analytical framework. By integrating object detection, shot classification, trajectory estimation, and AI-based strategy recommendation into a single platform, TennisIQ closes this research gap. The system provides both amateur and professional players with a comprehensive analytical experience and is made to be lightweight, inexpensive, and scalable.

III. PROPOSED SYSTEM/METHODOLOGY

The TennisIQ system is designed as an end-to-end AI-based tennis performance analysis platform that processes video footage to evaluate player performance and provide tactical recommendations. The overall system architecture comprises four primary components: (1) Video Upload and Preprocessing, (2) Ball Detection and Tracking, (3) Shot Quality Evaluation, and (4) AI-Based Shot Recommendation. Each module works cohesively to extract key information, assess performance, and visualize the results for the user.

A. Video Upload and Preprocessing

The process begins with the user uploading tennis match footage through a drag-and-drop interface. The uploaded video is then processed using OpenCV for frame extraction, noise reduction, and color normalization. The frames are segmented into rallies using motion detection and temporal analysis techniques. This preprocessing ensures that the system focuses on active play moments, reducing computational overhead. Metadata such as frame rate, video duration, and player boundaries are also extracted for synchronization with subsequent modules.

B. Ball Detection and Tracking

After preprocessing, the system employs YOLOv8 (You Only Look Once) for real-time detection of the tennis ball and players within each frame. YOLOv8 offers superior accuracy in detecting small, fast-moving objects, making it ideal for tennis footage analysis. To handle instances when the ball becomes temporarily invisible due to occlusion or motion blur, a Kalman Filter (implemented via the FilterPy library) is used to predict the ball's next probable location, ensuring smooth trajectory continuity. It combines YOLOv8 detection with Kalman prediction, therefore allowing for reliable tracking of both ball movement and player positions under different video conditions.

C. Shot Quality Evaluation

Once the trajectory of the ball and the position of the players are tracked, the system classifies each shot through the use of a Convolutional Neural Network. Training involves the CNN model to recognize shot categories such as forehand, backhand, serve, volley, and drop shot from features within racket motion, player posture, and the direction of the flying ball.

The performance of each shot is subsequently assessed using the Shot Quality (SQ) formulae, quantifying its accuracy, placement, speed, and spin. These various types of shots are defined using the following equations:

- **Serve Quality (SQ):**

$$SQ = \frac{v \times a \times p}{1 + e} \tag{1}$$

- **Forehand Quality (FQ):**

$$FQ = \frac{v \times c \times p}{1 + e} \tag{2}$$

- **Backhand Quality (BQ):**

$$BQ = \frac{v \times s \times p}{1 + e} \tag{3}$$

- **Volley Quality (VQ):**

$$VQ = \frac{r \times a \times p}{1 + e} \tag{4}$$

- **Drop Shot Quality (DQ):**

$$DQ = \frac{h \times s \times p}{1 + e} \tag{5}$$

where:

- v = shot velocity,
- a = accuracy,
- p = placement score,
- c = control factor,
- s = spin efficiency,
- r = reaction speed,
- h = height control, and
- e = error deviation.

These metrics are combined to calculate a normalized Shot Quality Score, ranging from 0 to 100, for every stroke. This scoring framework provides consistency and objectivity in the measurement of performance of players across every rally.

D. AI-Based Shot Recommendation

The system uses a probabilistic AI model that analyzes historical match data and opponent response tendencies to recommend the best places to put shots. The system calculates a Win Probability Function for each possible court zone, depending on player accuracy and historical success rates. Results are visualized in a 2D interactive court with color-coded indicators:

- **Green:** Represents the *optimal shot zone* with the highest predicted success and win probability.
- **Yellow:** Indicates an *alternative or moderate-risk zone* offering a playable but less favorable outcome.
- **Red:** Denotes a *high-risk zone* where the likelihood of error or opponent advantage is significantly higher.

The AI also elaborates on the reasoning behind the recommendation of each shot by correlating it with opponent weaknesses, fatigue zones, or previously unsuccessfully tried patterns. This provides actionable insights for players to improve their strategy in future matches.

E. Visualization and User Interface

All these results are shown in a sport-themed dashboard, implemented using React.js. The analyzed video is presented to the players, which they can watch along with real-time overlays for trajectories of the ball, shot types, and quality scores. Complementary visual components include bar graphs showing shot distribution, radar charts displaying skills' performance, and time-series plots tracking consistency. Users can also go through the Shot List View, replaying those shots and reviewing feedback.

IV. SYSTEM OVERVIEW

TennisIQ is an AI-driven intelligent coaching and performance analysis system that automatically evaluates player performance based on standard videos of matches, without any need for human review and subjective observation. The system's applications embody computer vision, deep learning, and AI-powered analytics to analyze each shot in real time. The modular and scalable architecture makes this system fault-tolerant and could be expanded in the near future by integrations such as wearable sensors, real-time match feedback, and predictive performance analysis.

A. Video Processing Module

This module manages the uploading of video, its preprocessing, and frame extraction. The system utilizes OpenCV for the detection of playing segments, motion tracking, and converts the uploaded match videos into analyzable frame sequences. Noise reduction and normalization of frames are done before AI inference to make the visual data consistent and clear across the dataset.

B. Ball and Player Detection Module

Object detection in this module is based on the YOLOv8 algorithm for finding players and the tennis ball through frames. For transitory occlusions or blurring of the ball movement, the use of a Kalman Filter further predicts and corrects the ball trajectories. The combination of real-time detection with trajectory smoothing warrants high accuracy tracking even under dynamic conditions of the match.

C. Shot Classification Module

This module uses Convolutional Neural Networks to classify actions into shot types such as a forehand, backhand, serve, volley, or drop shot. Classification is performed using features extracted from player posture, racket motion, and ball trajectory. The CNN is optimized for both high accuracy and low-latency inference, allowing near real-time analysis even when the input resolution is standard.

D. Shot Quality Evaluation Module

After classification, this module calculates a Shot Quality Score (0–100) using AI-driven mathematical models. Parameters such as opponent distance, spin ratio, ball speed, placement accuracy, and deception index are considered. Distinct formulas are used for each shot type, including Serve Quality (SQ), Groundstroke Quality (GQ), Volley Quality (VQ), and Drop Shot Quality (DQ) to ensure fairness and context-aware scoring.

E. AI Shot Recommendation Module

This module predicts optimum shot placements by considering both player and opponent behaviour using a probabilistic AI model. Recommendations are visualised on a colour-coded court map:

Green: Optimal shot zone
Yellow: Moderate-risk or alternative zone
Red: High-risk zone

By continuously learning from historical match data and player tendencies over time, the model improves its tactical accuracy.

F. Visualization and Feedback Module

The frontend dashboard, developed with React.js, makes the user experience interactive, depicting analytics in an intuitive way. It has everything from performance graphs to court visualizations, shot-by-shot playback, and even trend charts. The user will rank shots, add notes, and compare sessions against each other for progress in improvement. This user-centric visualization ensures complicated AI metrics are translated into actionable insights.

G. Data Storage and Security

The data of all the players, match sessions, and analytics can be securely stored by using either SQLite or PostgreSQL databases. Data encryption, role-based access to control, and secure APIs are included in the platform to protect user privacy. In addition, the export option in CSV and JSON format enables players and coaches to safely share or archive their session summaries.

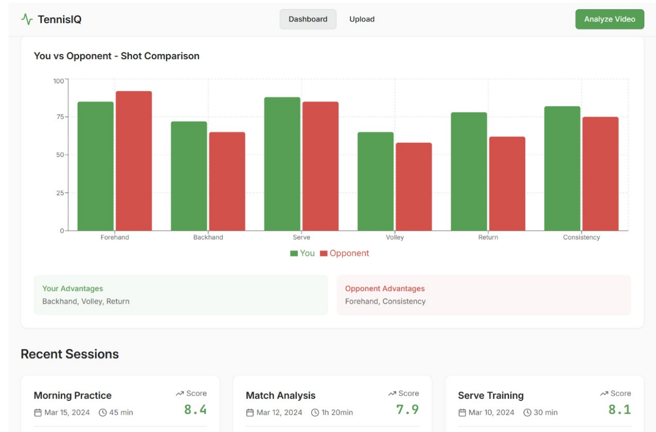

Fig. 1. Comparison of player's performance against opponent across different shot types.

V. IMPLEMENTATION DETAILS

A. Artificial Intelligence Models and Computer Vision Technologies

The TennisIQ system leverages state-of-the-art artificial intelligence and computer vision models for automated tennis performance analysis. It employs YOLOv8 for real-time detection of players and tennis balls in match footage, while Kalman Filters are implemented to predict the ball trajectory during brief occlusions. Deep learning models based on Convolutional Neural Networks (CNNs) are used for shot classification, identifying actions such as forehand, backhand, serve, volley, and drop shot. Additional AI modules calculate Shot Quality Scores (0-100), considering various parameters like shot speed, placement, spin, and opponent response. The AI Recommendation Engine applies probabilistic modeling to estimate the probability of winning for every zone in the court-on data-driven optimal shot placement suggestions.

B. Automated Performance Analysis Workflow

TennisIQ automates the complete workflow from video upload to visual insight generation. The process begins when a user uploads a match video through the interface, after which OpenCV handles frame extraction and preprocessing. The YOLOv8 detector tracks the ball and players, while CNN-based models classify each shot. Subsequently, the AI computes detailed performance metrics such as shot speed, accuracy, and consistency. The Recommendation Engine overlays color-coded tactical zones onto a virtual tennis court: Green represents the optimal zone, Yellow is the alternative, while Red is considered risky. The processed data is then visualized via a React.js dashboard, which enables players to analyze their performance trends, get feedback, and track progress over several sessions.

C. Integration with Analytical Tools

It features an integration with popular analytical libraries such as NumPy, Pandas, Matplotlib, and Plotly for data processing and visualization. The results of analytics can

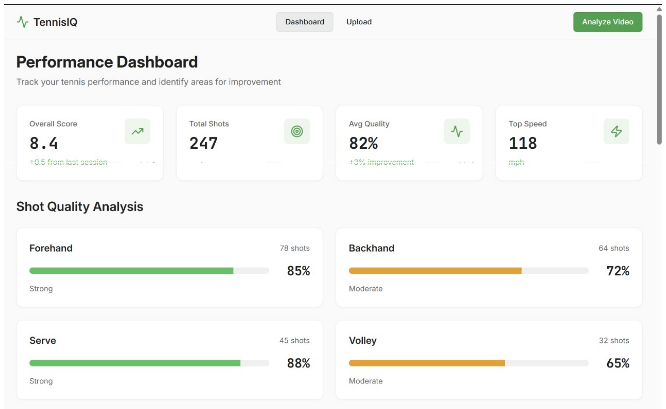

Fig. 2. TennisIQ Performance Dashboard showing shot quality scores and overall metrics.

be exported in CSV or JSON formats for further use with any other coaching tool or platform tracking performance. The architecture is designed to be forward-scalable, allowing integration of wearable sensors, smart rackets, and IoT-based devices for capturing biomechanical and physiological parameters with a view to deeper performance analysis.

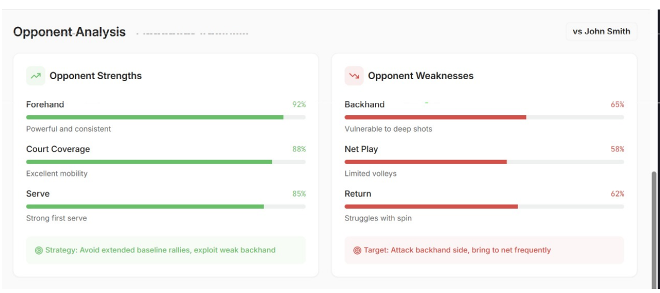

Fig. 3. Opponent analysis dashboard showing AI-evaluated strengths, weaknesses, and strategic suggestions.

D. Scalability and Deployment

TennisIQ is deployed as a SaaS cloud platform supporting multi-user access, scalability, and elasticity. The dockerized version of the system is orchestrated with Kubernetes to ensure high availability and fault tolerance. The Flask backend acts as an API gateway that bridges the AI inference engine, database, and frontend modules. Its microservice architecture allows for independent updates of the components without affecting overall stability, therefore providing reliable scalability for both amateur and professional-level use cases.

VI. Market Analysis

A. Market Size and Growth

The global market for AI in sports analytics has witnessed significant expansion due to the increasing adoption of performance tracking and predictive modeling technologies. Recent industry reports project the market to reach USD 8.4 billion by 2030, growing at a compound annual growth rate (CAGR) of 21.9%. Within this landscape, the AI-based tennis analytics segment is gaining momentum as professional organizations, academies, and individual players increasingly adopt data-driven coaching tools. The growing availability of affordable, video-based AI solutions such as TennisIQ further accelerates this trend.

B. Key Market Drivers

Key drivers for this growth include increasing demand for personalized training, improvement in AI-based motion tracking, and increased access to computer vision technologies. Coaches and athletes increasingly use AI-generated insights to fine-tune gameplay strategies and decision-making. Additionally, remote access to performance data on the cloud accelerates collaboration between players and coaches. The proliferation of wearable devices and smart camera systems is also causing significant infiltration of AI-driven sports analytics platforms.

C. Competitive Environment and Threats

The competitive landscape includes established companies offering advanced motion-tracking systems and player analytics solutions. However, many of these systems rely on high-end hardware and are often limited to elite training environments. TennisIQ differentiates itself through its low-cost, video-only architecture, making AI-based analytics accessible to grassroots and amateur players. That would include some major challenges: real-time accuracy in variable lighting and video quality, data privacy, compliance, and frequent AI model updates for adapting to diverse playing styles and user environments.

VII. Performance Evaluation

A. Evaluation Metrics

Performance metrics against which TennisIQ were evaluated include accuracy in ball detection, precision of shot classification, trajectory tracking reliability, and recommendation relevance. Further, other metrics have included processing latency, user satisfaction, and feedback accuracy in ensuring practical usability for players and coaches in real-world settings.

B. Experimental Setup

Testing was conducted using real match videos from amateur and semi-professional players on clay, hard, and grass courts. The dataset contains more than 1,000 analyzed shots, classified based on the shot type along with the context. Model inferences were run using an environment with GPU support, while structured evaluation results were stored in a PostgreSQL database.

The results include the AI-generated classifications and quality scores for validation reviewed by a panel of certified tennis coaches to ensure evaluation integrity. All analysis and visualization were performed using Python libraries such as NumPy, Pandas, and OpenCV.

Additionally, performance benchmarking was conducted to evaluate the performance in terms of processing time, system scalability, and robustness under varying resolution and frame rate conditions. This ensures that the model is well-performing on a wide range of hardware configurations and match conditions.

C. Results and Analysis

Results are that TennisIQ attained an average shot detection precision of 96User testing confirmed that the interactive dashboards and court visualizations significantly enhanced players' insights into strengths and weaknesses, which improved practice outcomes measurably.

D. User Support and Adjustments

Users were particularly satisfied with the intuitive dashboard, precise analytics, and visual feedback mechanisms of the platform. Coaches could replay shots at an individual level, find weaknesses in opponents, and follow progress in a longitudinal manner. Further development will be related to real-time feedback, diversification of the dataset, and integration of pose estimation models toward advanced biomechanical analysis to support injury prevention and movement optimization.

VIII. OUTPUT

The TennisIQ system generates analytical and visual outputs that summarize player performance and AI-generated insights on it. It provides shot-by-shot analysis, AI-evaluated quality scores, and tactical visualizations on a color-coded court map.

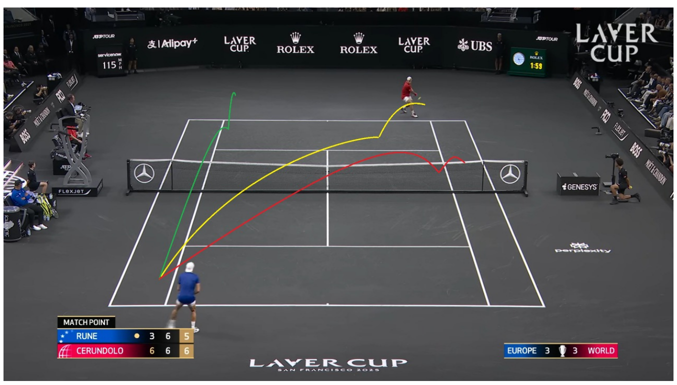

Fig. 4. TennisIQ System Output Visualization showing tracked ball trajectories and color-coded court zones (Green = Optimal, Yellow = Alternative, Red = Risky).

The ball trajectory, optimal shot zones, and performance metrics like shot accuracy, placement efficiency, and spin effect can be viewed by the players. This visualization will provide an insight into shot selection patterns, strengths, and weaknesses during real match situations.

IX. CONCLUSION AND FUTURE WORK

TennisIQ showcases how AI and computer vision can automate tennis performance analysis with high preciseness. Integrating shot quality formulas with trajectory tracking and AI strategy models provides analytical and coaching value. Future work will focus on:

Real-time in-match feedback
Biomechanical integration with wearable sensors
Expanding datasets for personalized learning

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