Development of Real-Time 5G-Enabled Video Analytics for Soccer Juggling Performance Evaluation

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***Abstract*—Soccer juggling is a crucial skill that helps players improve their ball control, coordination, and overall game performance. However, traditional ways of assessing juggling ability often rely on subjective opinions, which can lead to inconsistencies in player development. This study presents a more objective approach, using motion tracking and machine learning to evaluate juggling performance with greater accuracy. By collecting data from players of different skill levels, we analyzed key aspects such as juggling frequency, stability, and height control. A machine learning model was then trained on these features, allowing it to classify players' juggling proficiency with high accuracy. The results highlight the potential of automated evaluation systems to provide consistent, data-driven feedback, helping players refine their skills and improve their training.**

I. Introduction

Soccer juggling is a key skill in player development, enhancing ball control, coordination, and overall mastery of the game. Traditionally, coaches have assessed juggling ability based on their own judgment, which can be inconsistent and subjective. However, with recent advancements in sports technology, data-driven evaluations are becoming a more practical and accurate way to measure performance.

Recent studies have investigated the use of motion capture systems, wearable sensors, and artificial intelligence to analyze different aspects of sports performance. These technologies allow for real-time data collection, tracking factors like juggling frequency, ball trajectory, and stability. While these innovations have been explored, they have rarely been applied specifically to evaluating soccer juggling. This study aims to address that gap by developing a machine learning-based system to objectively assess juggling skills. By using motion tracking data and sophisticated algorithms, the goal is to enhance training methods and provide reliable, data-driven insights for both players and coaches.

II. Methodology

The overall methodology of this work is illustrated in Fig. 1,reffig:overall encompassing requirement analysis, design concept, implementation, testing, and improvement.

Fig. 1. Flowchart of the overall process of this research

A. *Requirement Analysis*

The Requirement Analysis phase plays a critical role in developing an effective soccer juggling evaluation system. It started with an in-depth review of current training methods, gathering feedback from both coaches and players to pinpoint the key elements needed to assess juggling skills. Key performance indicators like ball control, consistency, and precision were identified as essential factors for evaluation. To ensure the system meets real-world training needs, it was also compared with existing sports analysis tools. This comparison helped define the necessary hardware and software, such as motion tracking sensors and data processing algorithms. By establishing clear specifications, the system is built to provide reliable and objective assessments that aid in player development.

MODEL	ACCURACY	SPEED	Suitability for Real-Time
OpenPose	High	Low (~5-10)	Not ideal (High latency)
MediaPipe	Medium	High (~30+)	Good (Lightweight)
YOLO	High	Very High (~60+)	Best (Optimized for real-time)

Fig. 2. Model selection criterias for object detection and pose estimation

The Design Concept phase is crucial for creating an effective soccer juggling evaluation system. During this stage, the system's framework is carefully structured, with thoughtful selection of motion tracking technologies and the development of strong data processing methods to analyze juggling performance.

A key focus is on ensuring accuracy, delivering real-time feedback, and making the system user-friendly. By prioritizing these factors, the design is seamlessly integrated into player training routines, offering valuable insights that support skill development and enhance overall performance.

B. Implementation

During the implementation phase, the design is transformed into a working system by integrating both software and hardware components. Motion tracking sensors are set up to precisely capture juggling movements, while machine learning algorithms analyze this data to assess key performance metrics. The system utilizes OpenCV for video frame processing and feature extraction, ensuring efficient image analysis [5].

The system is designed with a user-friendly interface, making it easy for players and coaches to access real-time feedback and in-depth performance insights. This seamless integration ensures the technology becomes a valuable resource for skill improvement and training.

1) Model Selection: Three models—YOLO, MediaPipe, and OpenPose—were compared based on criteria such as detection accuracy, computational speed, and real-time processing capability.

TABLE I
MODEL SELECTION CRITERIAS

MODEL	ACCURACY	SPEED	Suitability for Real-Time
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After assessing different models, YOLO was chosen for its optimal balance of speed and accuracy, making it the most suitable option for tracking soccer juggling movements in real time. Its efficiency in detecting fast-moving objects gives it an advantage over alternatives like MediaPipe and OpenPose, which either struggle with consistent ball detection or demand high computational resources for pose estimation. YOLO's deep convolutional neural networks enhance its performance, aligning with recent advancements in deep learning-based object detection [4].Additionally, Fast R-CNN's contributions to object detection methodologies were considered during evaluation, as it provides insights into improving detection efficiency and accuracy [3].

Once chosen, YOLO was seamlessly integrated into the system alongside motion tracking sensors and a user-friendly interface. This combination provides players and coaches with real-time performance feedback, enhancing training and skill development.

2) Data Flow Process: The data flow process for the soccer juggling evaluation system follows a well-defined pipeline, as shown in Fig. 3. This structured approach ensures that tracking, analysis, and performance metrics are handled in real-time.

Fig. 3. Flowchart illustrating the data flow process of the soccer juggling evaluation system

3) Juggling Evaluation and Detection Algorithm: The juggling evaluation and detection algorithm operates in a clear, step-by-step process, illustrated in Fig. 4. This ensures effective tracking, detailed analysis, and accurate feedback on the juggler's performance.

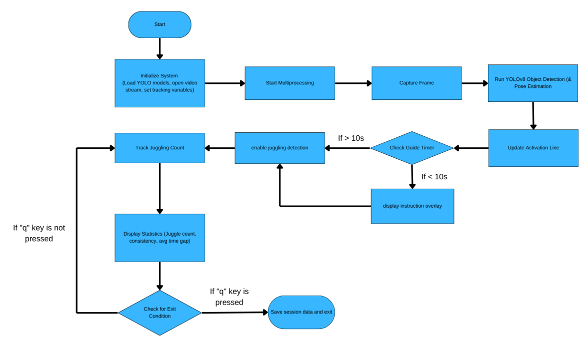

Fig. 4. Flowchart illustrating the data flow process of the juggling evaluation and detection algorithm

C. Key Performance Evaluation Metrics

These metrics provide an objective way to evaluate progress, enabling players to pinpoint areas that need improvement.

1) Juggling Count:

$$JC = \min\left(\frac{\text{Total Juggles}}{10}, 20\right) \tag{1}$$

2) Consistency Score: To create a single equation for Total Deviation, we need to incorporate the Median Absolute Deviation (MAD), Range, and Normalized Deviation, while also integrating the Scaling Factor and the final Consistency Score into one cohesive formula.

TABLE II
KEY PERFORMANCE METRICS FOR JUGGLING

Metrics	Description
Total Juggles	The number of times the player successfully keeps the ball in the air
Time Gap Between Juggles	The average time between each controlled touch
Juggling Consistency	The variation in ball height, indicating control over each touch
Total Session Duration	The overall time spent juggling.

$$\text{Total Deviation} = w_{\text{abs}} \log\left(1 + \text{MAD}_x^2 + \text{MAD}_y^2\right) + w_{\text{rel}} \log\left(1 + \left(\frac{\text{MAD}_x}{\text{Range}_x}\right)^2 + \left(\frac{\text{MAD}_y}{\text{Range}_y}\right)^2\right) \tag{2}$$

$$\text{Consistency Score} = \max\left(0, 1 - \frac{\left(\frac{N}{N+k}\right)^{0.5} \times \text{Total Deviation}}{10}\right) \tag{3}$$

Where N refers to the total number of data points in the dataset, while k is a constant used to adjust the scaling of the formula.

3) Time Gap Score: calculates the exponential decay based on the average time interval between each juggle

$$T_g = e^{-\left(\frac{G-1.0}{3.0}\right)} \tag{4}$$

4) Total Time Score: adjusts the total time by using a reference value of 120 seconds for scaling.

$$E_p = \min\left(\frac{T-120}{10}, 10\right) \tag{5}$$

5) Improvement Point (Tracking Progress): calculates the difference in average height between the last 5 successful juggles and the first 5 successful juggles, but only if there are at least 100 successful juggles, given $J \geq 100$

$$I_p = \begin{cases} 0, & \text{if } J < 10 \\ \max(0, \mu h_{\text{last5}} - \mu h_{\text{first5}}), & \text{if } J \geq 10 \end{cases} \tag{6}$$

6) Final Rating Calculation: is the total of the Juggling Count, Consistency Score, Time Gap Score, Total Time Score, and Improvement Point.

$$R = JC + C_s + T_g + E_p + I_p \tag{7}$$

D. Testing

The testing phase is vital to ensure the soccer juggling evaluation system works as expected. It involves both controlled experiments and real-world trials to validate the system's accuracy, responsiveness, and ability to classify juggling performance. The system's effectiveness is measured using key metrics like accuracy, precision, and mAP@50.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{8}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

(9)

$$\text{mAP@50} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i \text{ at IoU} \geq 0.5 \tag{11}$$

$$\text{mAP@50-95} = \frac{1}{N}\sum_{i=1}^{N} \frac{1}{10}\sum_{j=50}^{95} \text{AP}_i \text{ at IoU} = j/100 \tag{10}$$

E. Improvement

The improvement phase focuses on refining the system based on the results from testing. Significant optimizations included improving data processing, enhancing sensor accuracy, and reducing inference time. For instance, the system's frames per second (FPS) were boosted, and latency was reduced by streamlining data preprocessing and utilizing TensorRT. Additionally, multiprocessing was introduced to handle video processing, model inference, and post-processing in parallel, improving real-time performance.These updates made the system more responsive and accurate, which is critical for evaluating soccer juggling effectively.

III. RESULTS

A. System Performance & Accuracy

The validation process was carried out using a dataset consisting of four clean images, ensuring no background noise or corrupted data.

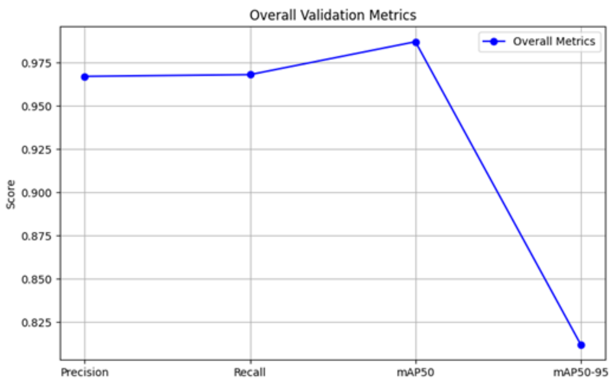

Fig. 5. Validation Metrics Result for Object Detection Model

The model's precision was 9.52%, while recall was 14.3%. The mAP@50 score was 5.51%, and mAP@50-95 was 3.51%, indicating that the model had difficulties in object detection and classification.

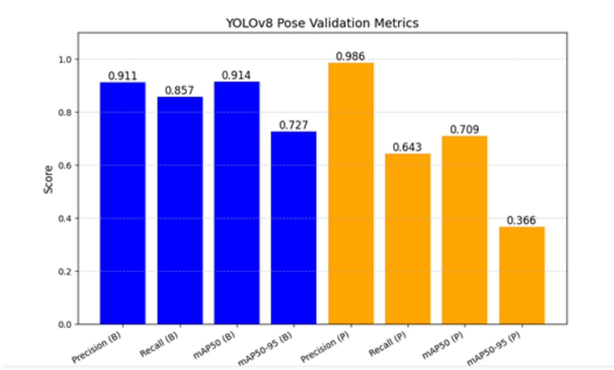

Fig. 6. Validation Metrics Result for Pose Estimation Model

The YOLOv8-pose model performed well in object detection but faced challenges in pose estimation. It showed a high bounding box precision (0.911) and recall (0.857), with an mAP50 of 0.914. However, pose estimation results were inconsistent, with keypoint precision at 0.986 but a recall of 0.643. This shows that the model sometimes missed keypoints, even when detecting them.

1) CPU & GPU Utilization: CPU usage ranged from 18% to 41%, while GPU utilization varied between 17% and 40%. Latency was between 246 ms and 328 ms, impacting real-time processing. FPS was relatively low (16.3 to 20.2), making smooth performance difficult.

Optimization of GPU usage and latency adjustments are necessary to enhance the system's efficiency.

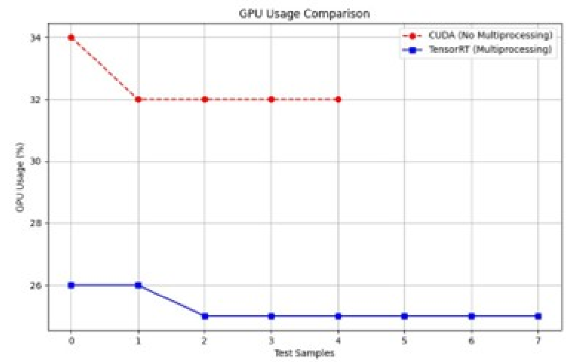

Fig. 7. GPU Usage Comparison between TensorRT and CUDA

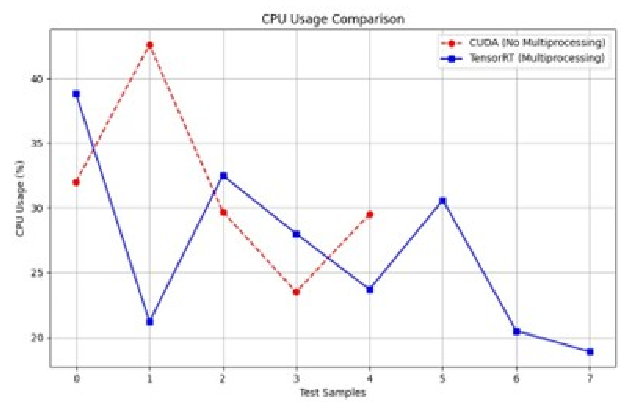

Fig. 8. CPU Usage Comparison between TensorRT and CUDA

2) FPS & Latency: Using TensorRT and multiprocessing drastically improved performance, reducing latency from 275.61 ms to 321.79 ms with CUDA to between 46.02 ms and 61.12 ms. This improvement translated into faster processing and a smoother real-time experience.

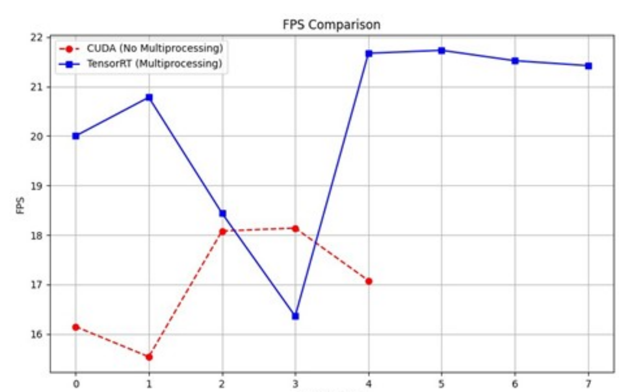

Fig. 9. FPS Comparison between TensorRT and CUDA

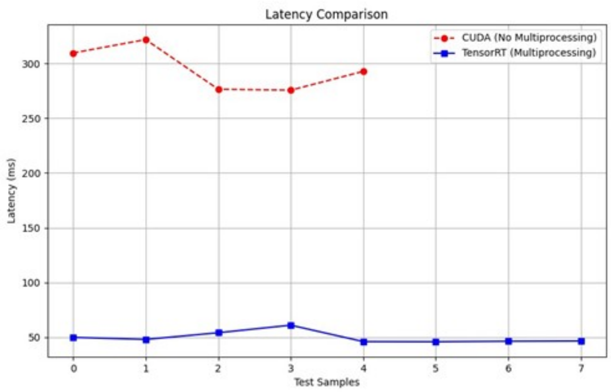

Fig. 10. Latency Comparison between TensorRT and CUDA

B. Scoring System Effectiveness

The system's effectiveness in evaluating juggling performance is clear. It captures both precision and recall, ensuring that juggling counts are both accurate and complete.

TABLE III
JUGGLING COUNT DATA (OBTAINED VS ACTUAL)

Juggling count	**Players**				
	1	**2**	**3**	**4**	**5**
Obtained	10	3	12	15	10
Actual	10	8	10	13	1

The table displays the juggling counts for five players, comparing the system's recorded values with the actual performance. Each column represents a different player, and the rows show the predicted (obtained) and real (actual) juggling counts, offering a clear view of the system's accuracy.

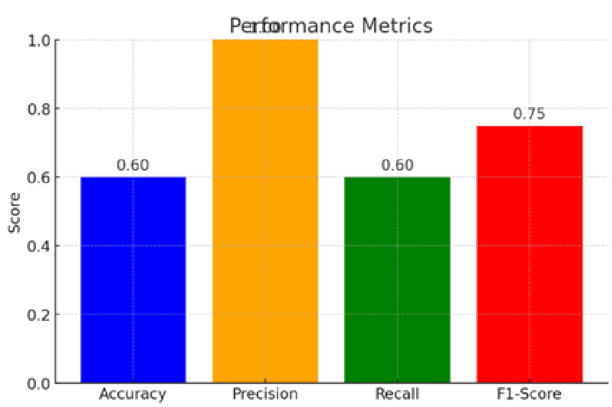

Fig. 11. Juggling Count Performance Metrics

The system's accuracy was 60%, with perfect precision but a recall rate of 60%. The F1-score was 0.75, indicating a balanced approach, though some errors were present. The mean absolute error (MAE) was 3.60, and the mean squared error (MSE) was 22.80.

1) Limitations: A major limitation was the inability to implement a 5G connection due to network policies. Instead, testing was conducted using Wi-Fi and LAN connections. Future versions could explore 5G integration for better real-time performance.

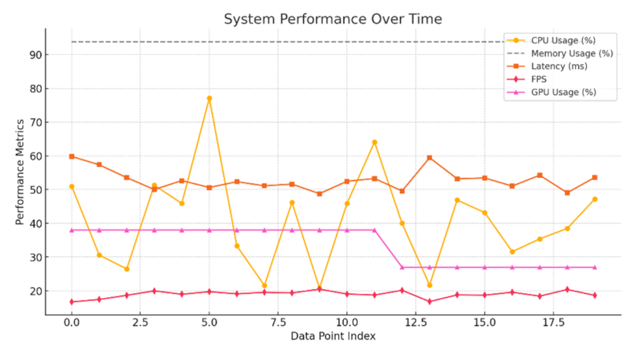

Fig. 12. System Performance on 4G Network Webcam

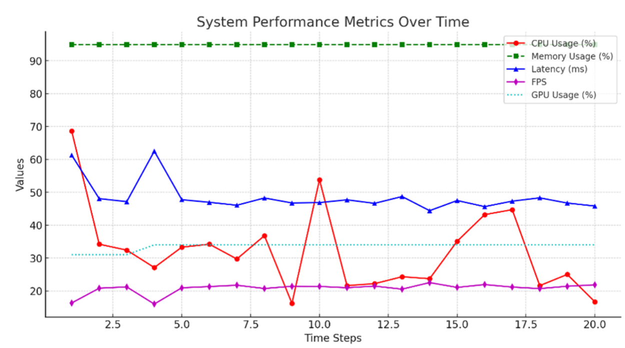

Fig. 13. System Performance on Wired Webcam

IV. CONCLUSION

This project successfully developed an automated system for evaluating soccer juggling using deep learning and computer vision. By utilizing YOLO for ball detection, optimizing performance with CUDA acceleration and multiprocessing, and improving real-time tracking, the system can now analyze juggling performance with higher accuracy and speed.

During development, challenges emerged, such as undetected hand catches, inconsistencies with player movement, and difficulty recognizing advanced tricks. To address these, optimizations were made, including better error handling, refined calculations using NumPy, and improvements to the activation line mechanism. These changes enhanced system stability and efficiency, enabling real-time tracking at 30-50 FPS with minimal delay.

While the system has become more reliable, there is still room for improvement. Future work could include tracking movements over time to recognize juggling tricks, fine-tuning the activation line to reduce inaccurate juggle counts, and enhancing ball detection in varied lighting. Adding AI-powered trick recognition would further advance the system and help players improve their skills.

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