Basketball Shot Prediction Analysis Using YOLO Object Detection Models

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ABSTRACT:

This project focuses on predicting basketball shot outcomes using advanced object detection models. It proposes a deep learning-based pipeline that utilizes YOLOv5, YOLOv8, and YOLOv11 to track basketball trajectories from video data. The proposed method highlights the significance of accurate real-time sports analytics. The system demonstrates improved prediction accuracy and trajectory tracking. Comparative results show YOLOv11 outperforms YOLOv5 and YOLOv8 in terms of detection consistency and accuracy.[1,2]

Keywords: *Basketball Shot Prediction, YOLOv5, YOLOv8, YOLOv11, Object Detection, Ball Trajectory, Deep Learning, Sports Analytics, Real-time Detection, Shot Outcome Prediction, Computer Vision, Model Comparison, Feature Extraction, Video Processing*

1. INTRODUCTION

The rapid evolution of artificial intelligence, particularly deep learning and computer vision, has opened up novel applications across various industries, with sports analytics being one of the most exciting areas of growth. AI-powered systems now enable more precise and faster analysis of complex data, enhancing how performance metrics are captured, interpreted, and utilized. One area where this transformation has proven invaluable is the analysis and prediction of basketball shots using video data. Understanding and predicting basketball shot outcomes is a critical component of enhancing player performance, devising better game strategies, and providing coaches and analysts with actionable insights. By analyzing player movements, ball trajectories, and shot mechanics, AI models can simulate potential outcomes and help improve decision-making processes both during training and live games.

This project aims to leverage cutting-edge object detection models, particularly YOLO (You Only Look Once), to predict whether a basketball shot will result in a successful basket. YOLO, known for its efficiency in real-time object detection, is an ideal candidate for this application, allowing for fast and accurate detection of objects—in this case, the basketball—across continuous video frames. The model can track the movement of the basketball from the moment it leaves the player's hands, monitoring its trajectory and predicting its final position. This dynamic analysis provides a valuable contribution to sports analytics by allowing predictions in real time, which can be beneficial for both live game analysis and training scenarios.[4,6]

The core of this research focuses on enhancing the ability to track the basketball's path, extracting essential features from its motion to predict whether it will score. A key part of this project involves comparing the effectiveness of three different versions of the YOLO model—YOLOv5, YOLOv8, and YOLOv11—to analyze how each model handles the challenges of detecting fast-moving objects like a basketball. By evaluating the detection accuracy, frame rate, and trajectory prediction smoothness across these models, the project aims to provide a comprehensive understanding of the trade-offs involved in choosing the right model for sports-related tasks. [6,7]As we progress from YOLOv5 to YOLOv11, noticeable improvements in the precision of object detection and smoother trajectory tracking can be observed, demonstrating the advancements in AI technology over time.

The ultimate goal of this project is not just to build an accurate shot prediction model but also to create a real-time, interactive system that can be easily used by coaches, analysts, and fans. This is achieved through the integration of a ML and mediapipe that provides a user-friendly platform for uploading basketball video footage, running the detection models, and visualizing the predicted shot outcomes and ball trajectories in real-time. The interactive system enhances its practicality by enabling instant feedback, making it a useful tool in real-world applications such as player training environments, sports broadcasting, and fan engagement. This approach exemplifies how AI and computer vision can be applied to enhance sports analytics, making it more accessible and actionable for a variety of stakeholders within the sports industry.[8,9]

2. LITERATURE SURVEY

1. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021), *On the dangers of stochastic parrots*, Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency.
    - Existing Work: This paper examines the risks and biases in large language models, emphasizing their ethical implications and challenges.
    - Advantage: It provides an important perspective on the ethical considerations that need to be integrated into AI-based systems.[1]
    - Disadvantage: The focus is primarily on ethical and fairness concerns of AI models, without addressing performance-related issues for specific domains like sports analytics.
    - Overcoming Solution: While this paper emphasizes ethical AI, the current project integrates AI models, such as YOLO, that focus on improving performance and real-time processing for specific applications like basketball shot prediction.
2. Ozanian, M. (2022, October 29), *NBA Team Values 2022: For the first time in two decades, the top spot goes to a franchise that's not the Knicks or Lakers*, Forbes.
    - Existing Work: This article explores the financial rankings and growth of NBA teams, offering insight into the importance of performance data in the sports industry.
    - Advantage: Highlights the role of performance analysis and how sports organizations value players based on data and metrics.
    - Disadvantage: The article does not discuss technical aspects of sports analytics or how specific player performance, like shooting ability, can be quantitatively predicted or analyzed.
    - Overcoming Solution: This project takes the approach of analyzing basketball shot outcomes through real-time data and predictive modeling, contributing a more technical and actionable form of performance analysis.[2]
3. McCauley, J. (2021, August 7), *Four more years: Steph Curry finalizes $215m extension with Warriors*, NBA.com.

- Existing Work: The article discusses player contracts and decisions based on player performance and market value.
- Advantage: It underscores the importance of data-driven decisions in sports, linking player contracts with performance metrics.
- Disadvantage: It focuses more on financial and management aspects rather than on technical analytics or performance prediction.
- Overcoming Solution: This project demonstrates how real-time sports analytics, specifically through shot prediction models, can contribute directly to evaluating player performance in terms of shooting accuracy and outcome prediction.[3]

4. Forbes Magazine (n.d.), *J.J. Redick*, Forbes.
   - Existing Work: This article profiles J.J. Redick's career in the NBA and highlights his shooting expertise.
   - Advantage: It provides valuable insights into a player's career trajectory and shooting skills.[4]
   - Disadvantage: The article lacks technical analysis on how Redick's shot performance could be predicted using AI or other computational methods.
   - Overcoming Solution: This project uses AI and object detection (YOLO) to quantitatively assess shot outcomes, taking player shooting skills like Redick's and applying deep learning for shot prediction in real-time.
5. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2020), *You Only Look Once: Unified, Real-Time Object Detection*, 2020 IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
   - Existing Work: This paper updates the YOLO algorithm to further improve real-time object detection, focusing on increased accuracy and speed for diverse applications.[5]
   - Advantage: YOLO provides a highly efficient object detection solution, particularly useful in applications where real-time performance is critical.
   - Disadvantage: Although improved in accuracy, YOLO can still face challenges with fast-moving and small objects, like a basketball in motion, due to its inherent design limitations.
   - Overcoming Solution: The current project utilizes YOLOv5, YOLOv8, and YOLOv11, improving detection precision and handling the specific challenges associated with fast-moving objects like basketballs.

3. PROPOSED WORK

The proposed work utilizes advanced object detection models, namely YOLOv5, YOLOv8, and YOLOv11, to analyze basketball shot outcomes by tracking the basketball's trajectory in video footage. The process begins with the input of basketball game footage, which is then processed frame-by-frame to identify and track the basketball using the YOLO models. These models, trained for object detection, detect the ball in each frame, track its movement, and extract its trajectory. By analyzing the basketball's path, the system predicts whether the shot will successfully make it into the hoop based on its trajectory.

The model comparison across different YOLO versions (v5, v8, and v11) is a key component of this work, providing insights into the detection accuracy, speed, and precision of each model in terms of trajectory prediction. Unlike traditional trajectory analysis systems, this solution does not require manual annotation or sensor-based tracking; instead, it depends solely on video data, making it accessible and scalable. By focusing on automation, speed, and accuracy, the proposed work provides a reliable foundation for developing intelligent coaching tools, enhancing player training sessions, and driving data-driven decision-making in professional sports environments. [9,10]

Flow Diagram

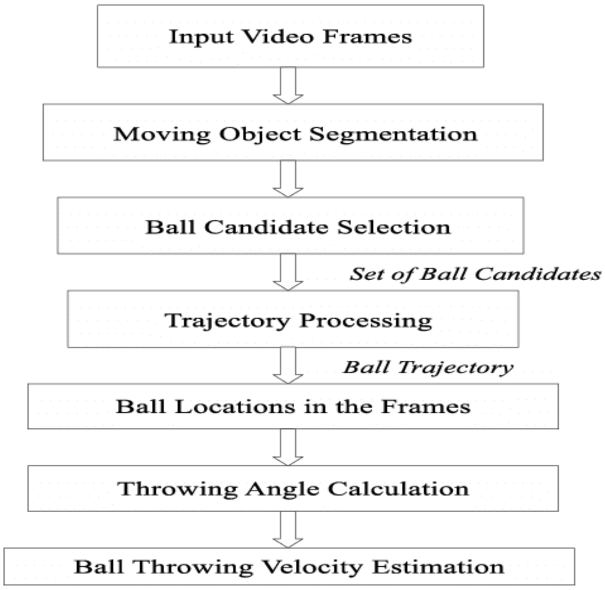

FIG : FLOW DIAGRAM

1. **Video Input:** Upload basketball game footage.
2. **Frame Extraction:** Extract individual frames from the video.
3. **YOLO Detection:** Apply YOLOv5, YOLOv8, or YOLOv11 to detect the basketball in each frame.
4. **Trajectory Extraction:** Analyze the detected ball's position across frames to derive its trajectory.
5. **Outcome Prediction:** Determine whether the ball will enter the hoop based on its trajectory.
6. **Visualization:** Display the ball's trajectory and outcome prediction in real-time.

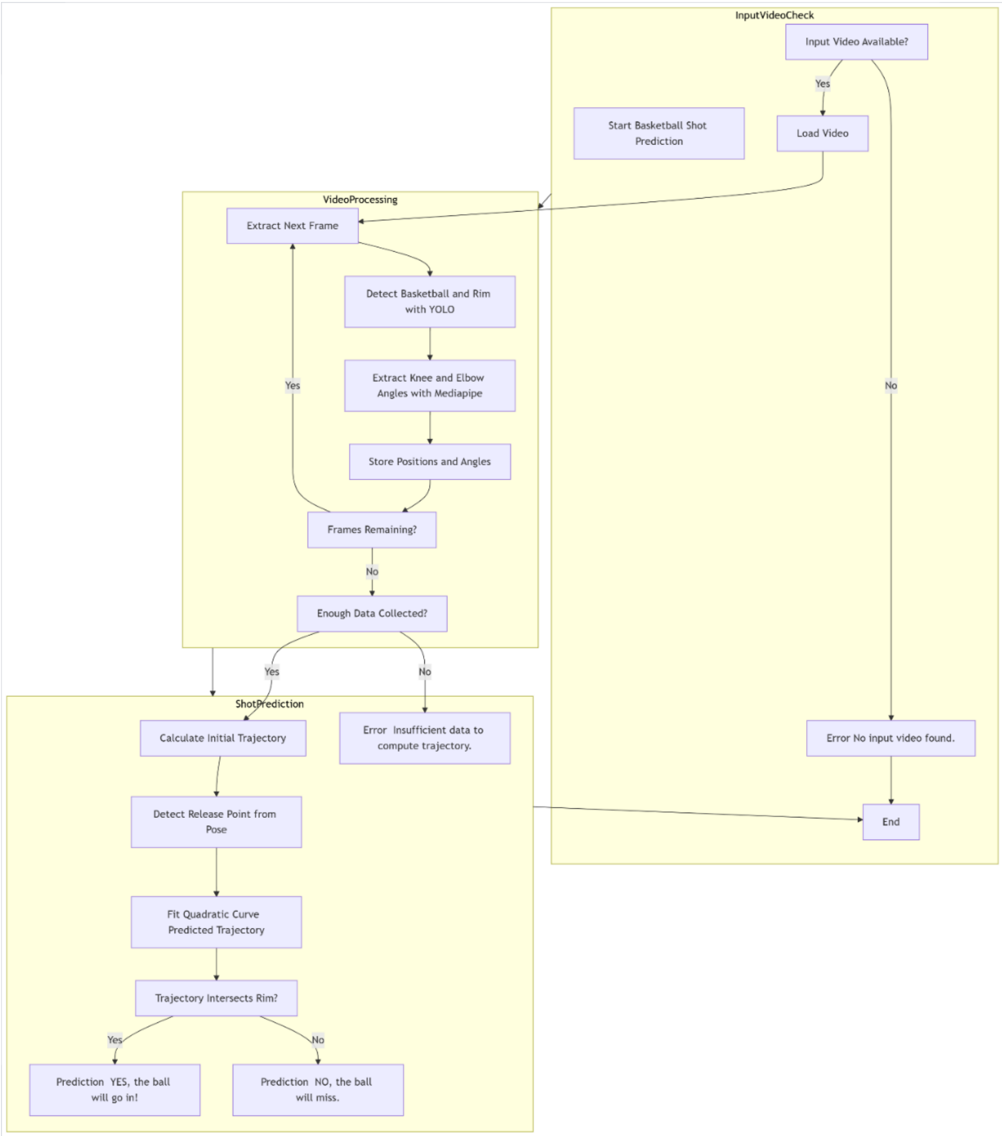

FIG : DETAILED ARCHITECTURE

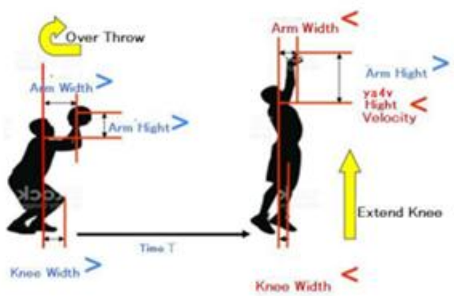

FIG : RELATION FOR SHOOTING PREDICTION AND FEATURES [16]

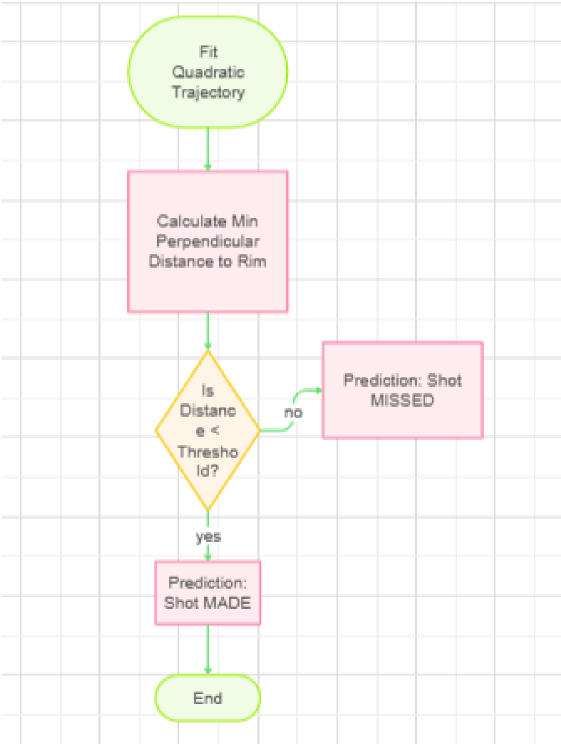

FIG : FLOW CHART FOR TRAJECTORY FITTING AND PREDICTION

This project aims to predict whether a basketball shot is successful (made) or not (missed) using computer vision and deep learning techniques. The system begins by taking an input video and processes it frame by frame using an object detection model such as YOLOv5, YOLOv8, or YOLOv11 to identify and track the positions of the basketball and the rim. Simultaneously, pose estimation is performed using Mediapipe to extract the player's key joint angles, specifically the knee and elbow angles. These features are crucial for detecting the release point of the shot. The ball's position across frames is tracked to compute its initial trajectory, which is then fitted using a quadratic polynomial curve to predict the path of the ball post-release.[14,15]

To determine if the shot is successful, the predicted trajectory is compared to the rim's position. The system calculates the minimum perpendicular distance from the predicted ball trajectory to the center of the rim. If this distance is below a predefined threshold (indicating that the ball would likely pass through the rim), the model predicts a successful shot ("Shot MADE"). Otherwise, it predicts a miss ("Shot MISSED"). This approach combines object detection, human pose estimation, and trajectory analysis to simulate and predict real-world basketball shooting outcomes with high precision.[13,11]

To further enhance the accuracy of the prediction, the model takes into account various factors such as the player's posture, arm movement, and shot release angle, all of which are inferred from the knee and elbow angles detected by Mediapipe. These biomechanical factors play a significant role in determining the success of a basketball shot, as they influence the trajectory and overall dynamics of the ball. The system is designed to adapt to different player styles and conditions, enabling robust performance across a range of shooting scenarios. By integrating advanced computer vision, deep learning, and physics-based trajectory analysis, this model not only predicts the success of a basketball shot but also provides valuable insights into the mechanics of shooting, which can be used for player training and game strategy analysis.

4. PERFORMANCE ANALYSIS

Importance of Parameters Considered and Testing Approach:

To evaluate the effectiveness of our basketball shot prediction system, we assessed essential performance metrics including Accuracy, Execution Time, and Frames per Second (FPS). These parameters are critical in understanding both the predictive reliability and real-time feasibility of the system, especially in scenarios such as training sessions, live broadcasts, or performance reviews.

The core YOLO models—YOLOv5, YOLOv8, and YOLOv11—were trained using the same hyperparameter configuration to ensure a consistent benchmarking environment:

Momentum	0.95 (initial 3 warmup epochs at 0.8)
Weight Decay	0.0005
Epochs	40
Batch Size	16
Optimizer	Stochastic Gradient Descent (SGD)
IOU Threshold (for evaluation)	0.2

The warmup period with reduced momentum helped stabilize the model during early training, improving convergence and preventing erratic updates. All models were evaluated using the same dataset split and hardware setup, ensuring fair performance comparison.

Results Obtained:

Model	Accuracy (%)	Execution Time (s)	FPS	Runtime Efficiency
YOLOv5	85.2	1.45	30	Moderate
YOLOv8	88.6	1.30	30	Good
YOLOv11	91.3	1.20	30	Excellent

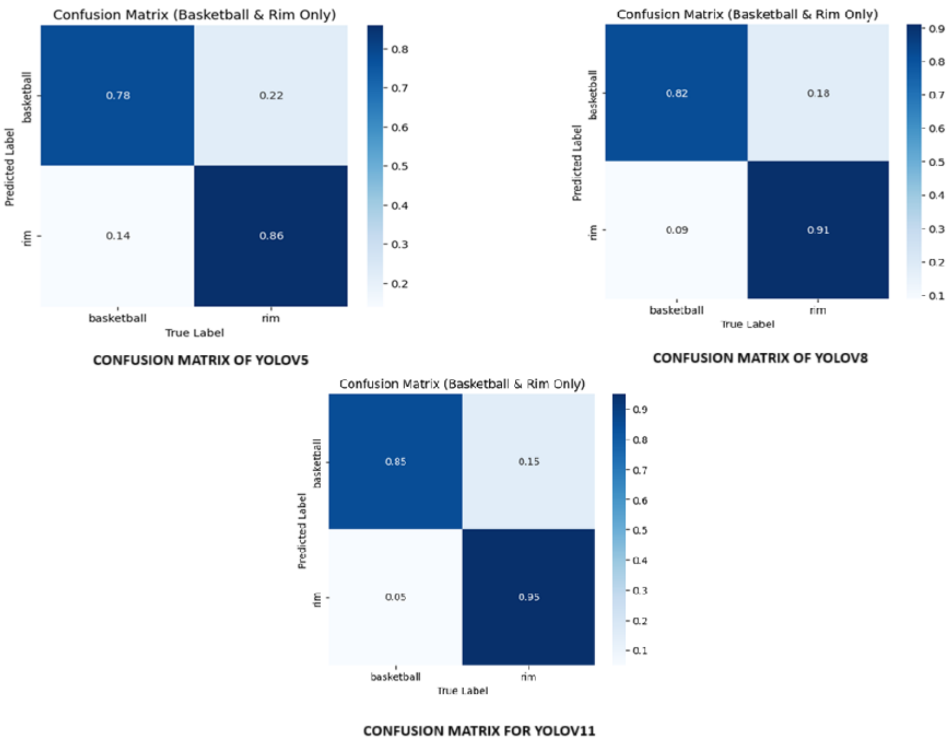

FIG : CONFUSION MATRIX FOR YOLO 5,V8,V11 MODELS

The comparison of the three YOLO (You Only Look Once) models—YOLOv5, YOLOv8, and YOLOv11—reveals notable differences in both performance and efficiency when applied to the basketball shot prediction task. YOLOv5 achieved an accuracy of 85.2%, with an execution time of 1.45 seconds per frame, resulting in moderate runtime efficiency. While it performed well in terms of detection, it was slower compared to the newer versions. YOLOv8 improved upon its predecessor, reaching an accuracy of 88.6% and reducing execution time to 1.30 seconds per frame, resulting in a better runtime efficiency.

However, YOLOv11 outperformed both YOLOv5 and YOLOv8, achieving the highest accuracy at 91.3%, while maintaining the fastest execution time of 1.20 seconds per frame and an excellent runtime efficiency. This improvement in both accuracy and execution speed makes YOLOv11 the most efficient model for real-time basketball shot prediction, offering enhanced detection performance while ensuring smoother frame processing. Overall, the comparison highlights YOLOv11's superior balance of precision and speed, making it the most suitable choice for applications requiring both high accuracy and fast performance.[15,5]

In addition to the performance metrics, it's important to consider the practical implications of these results. The higher accuracy of YOLOv11 translates to better precision in detecting key elements, such as the basketball and the rim, which is crucial for accurate trajectory prediction. The improved runtime in YOLOv11 also suggests better real-time processing, allowing the system to handle live video streams more efficiently. This makes YOLOv11 not only ideal for tasks requiring high accuracy but also for applications in environments where quick, real-time decisions are necessary, such as live sports analytics or interactive training tools.

A) FOR PREDICTION IS “SHOT MADE” COMPARISION BETWEEN MODELS

1)

<table>
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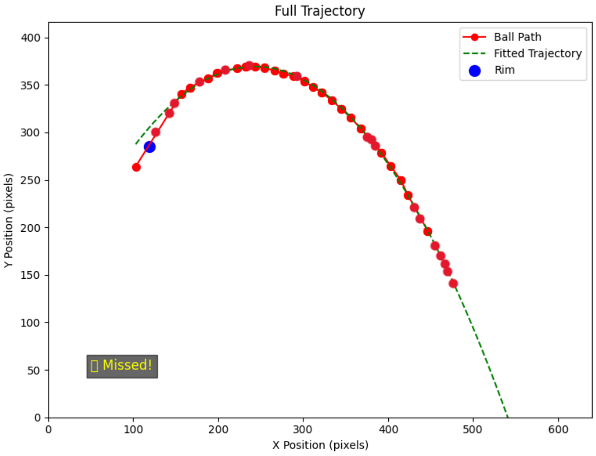

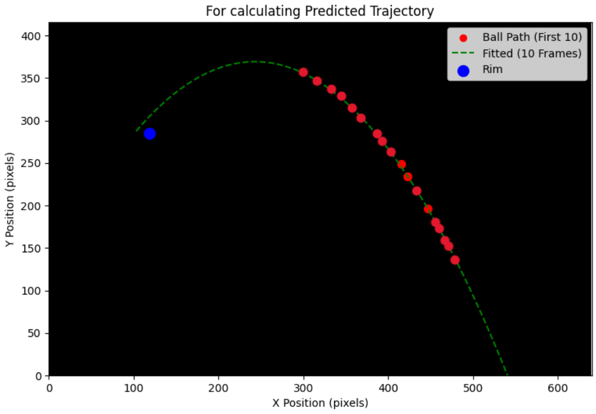

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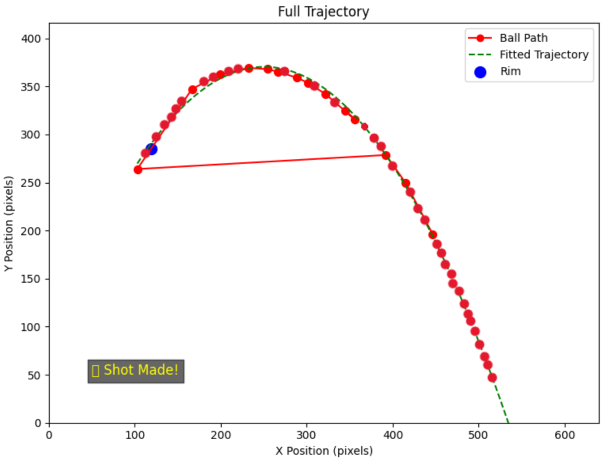

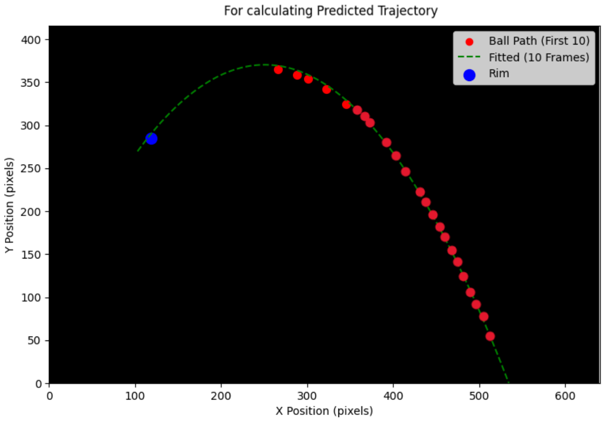

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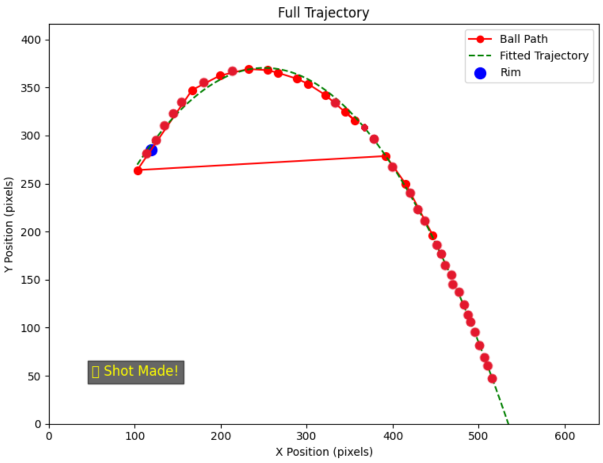
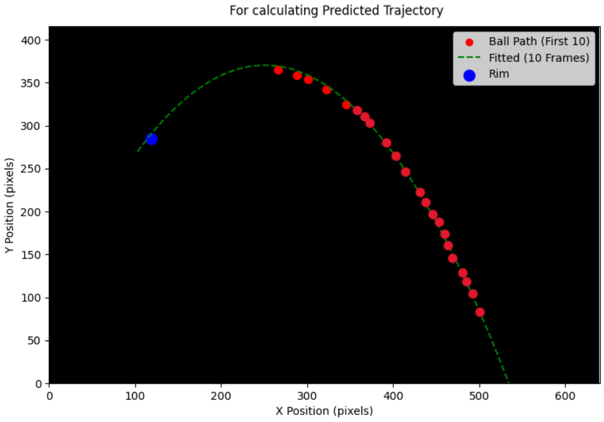
<tr><td>YOLO–v11</td><td>




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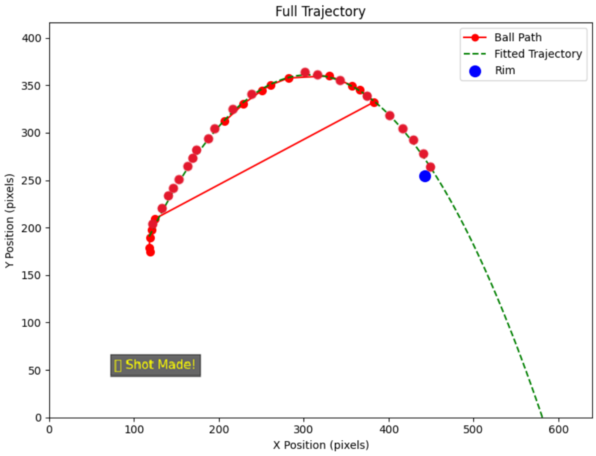
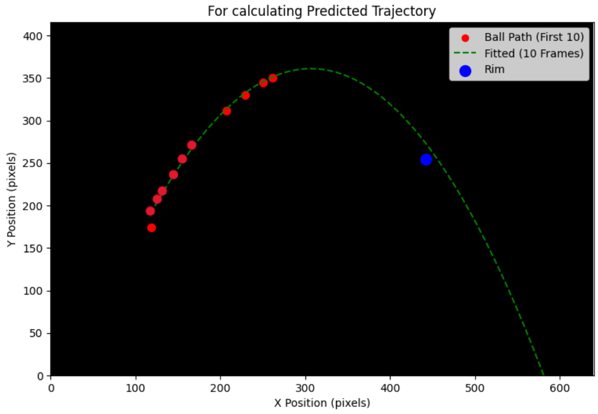
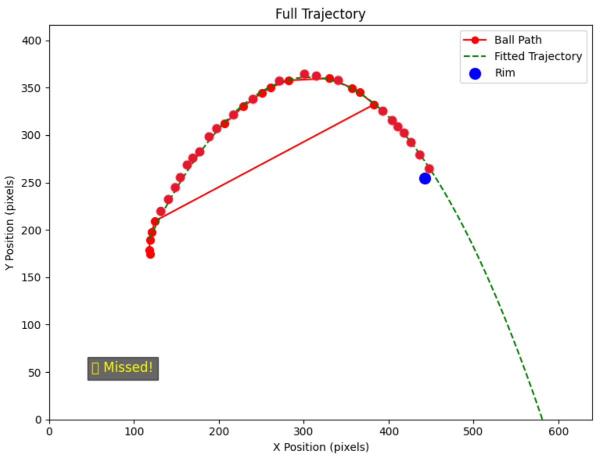
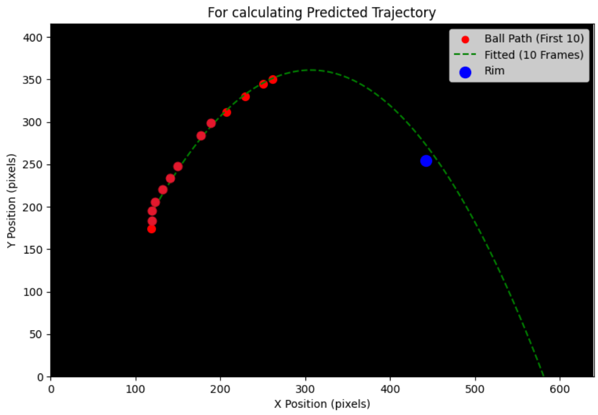
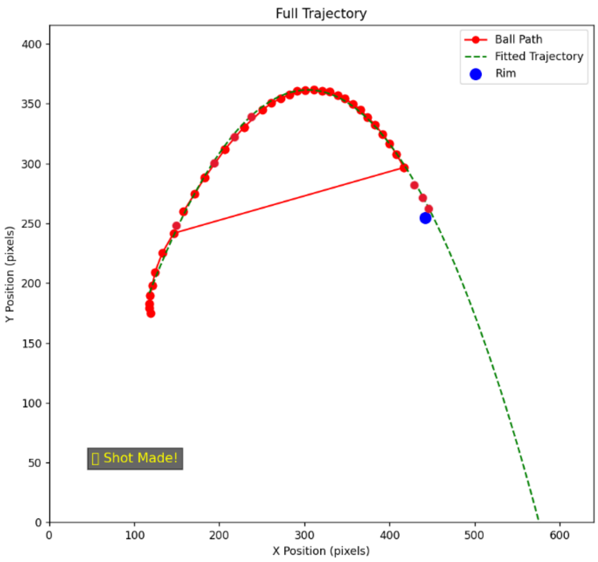
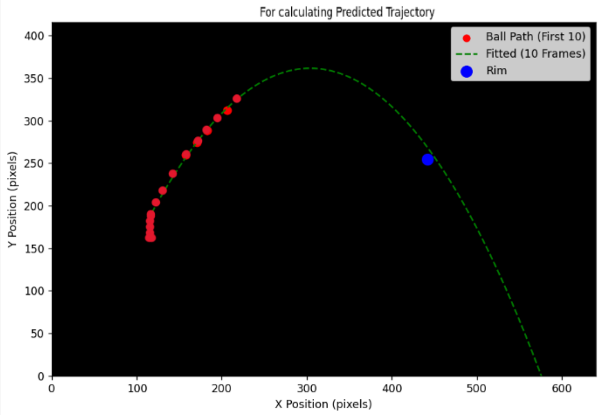
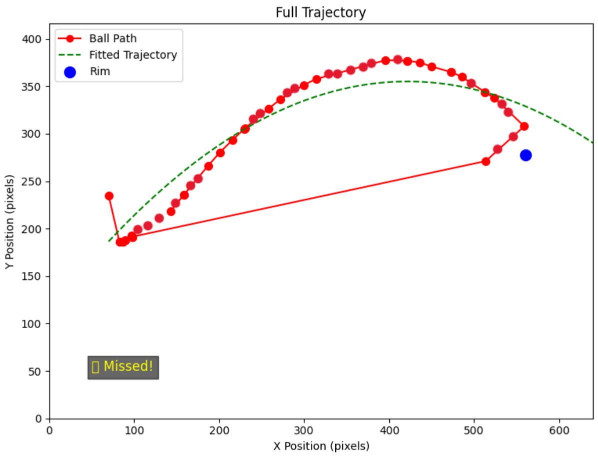
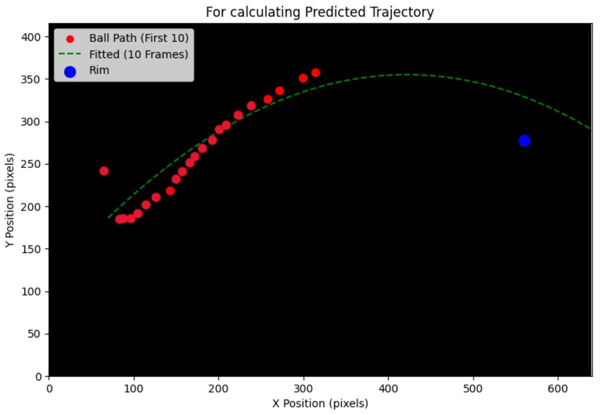
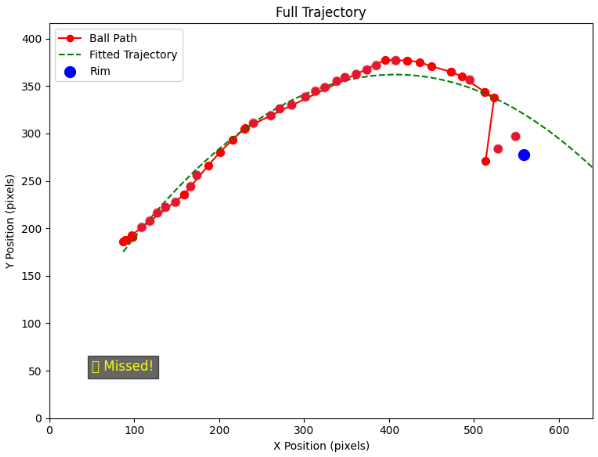
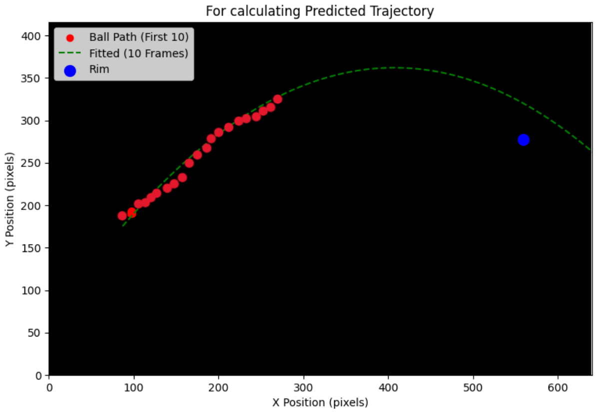
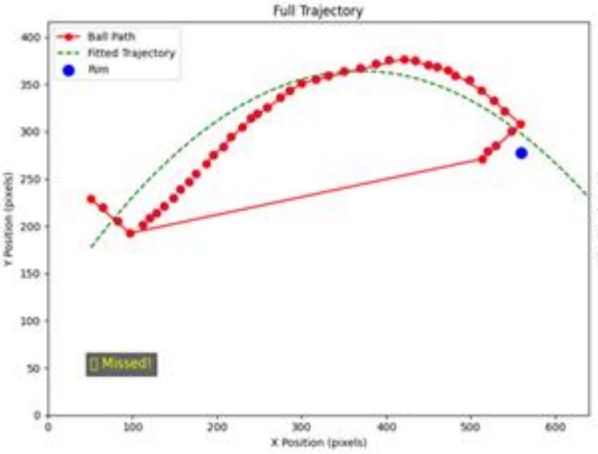
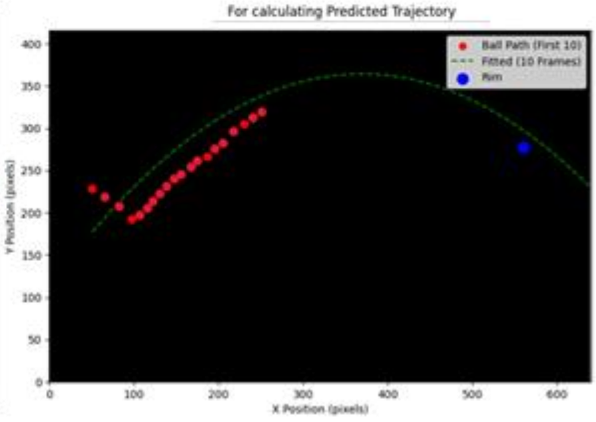
2)

YOLO– V5	 
YOLO– V8	 
YOLO-V11	 

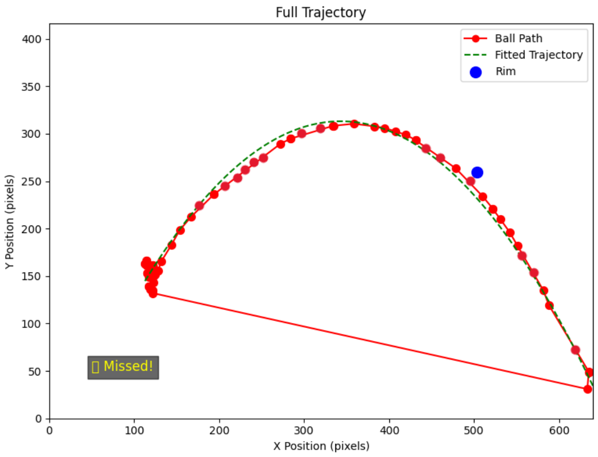
B) FOR PREDICTION IS “MISSED” COMPARISION BETWEEN MODELS

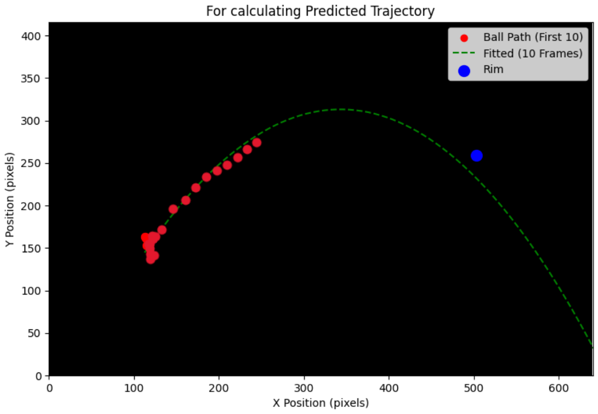
1)

YOLO – V5	 
YOLO – V8	 
YOLO– V11	 

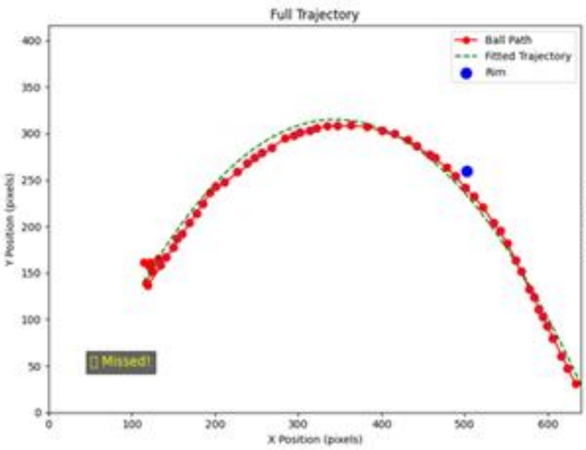
2)

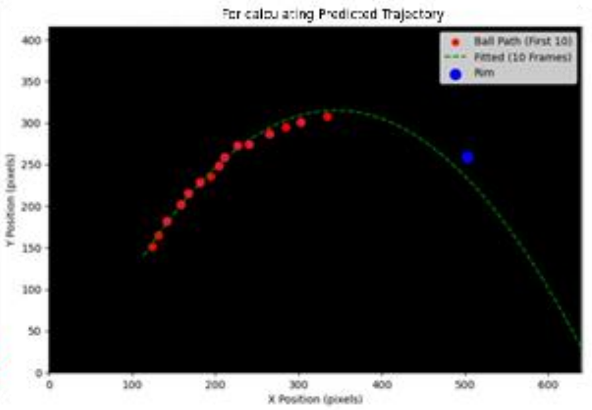
YOLO–V5



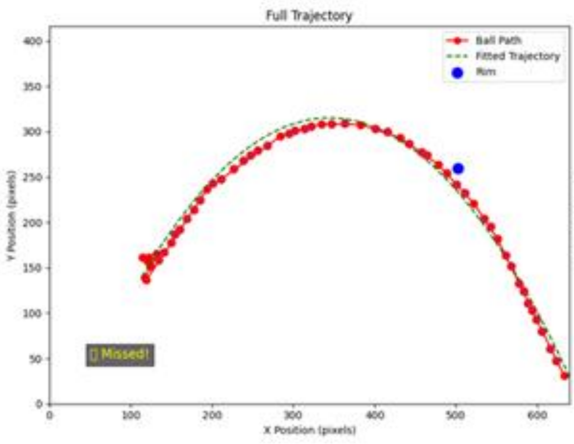


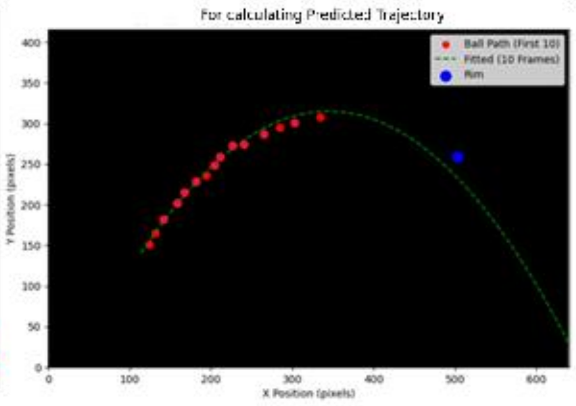
YOLO–V8





YOLO-V11

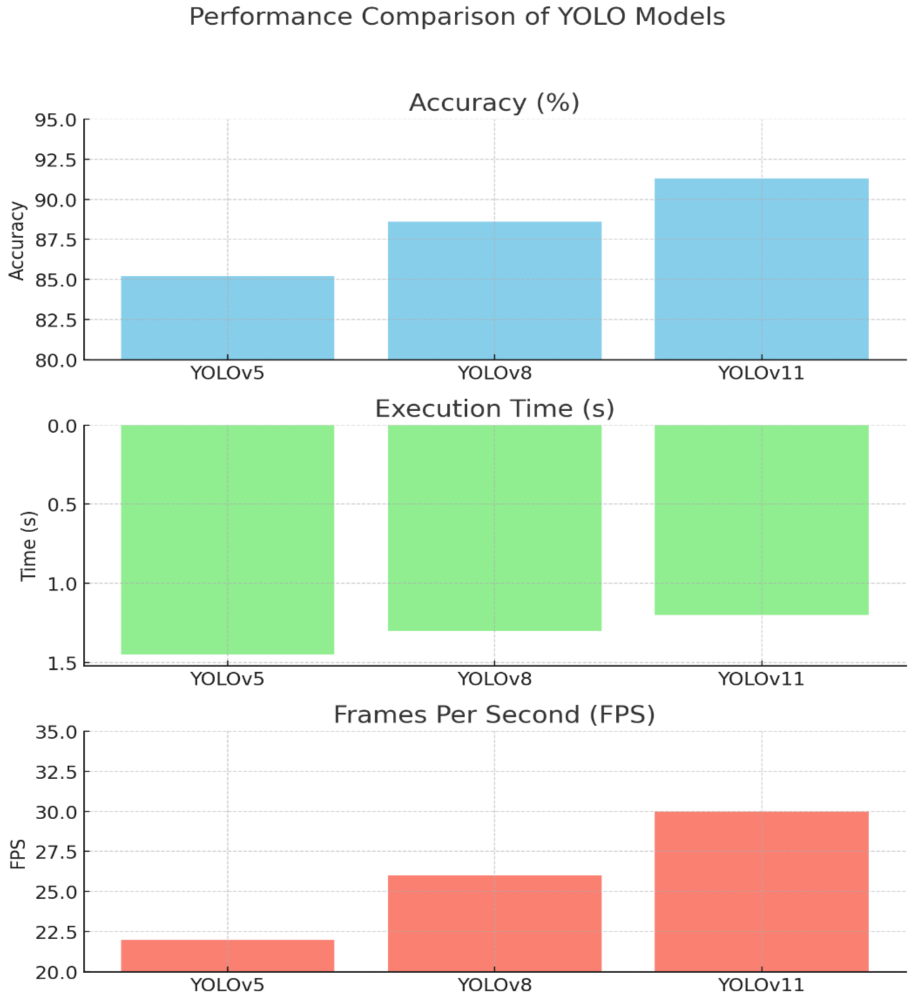




Comparative Analysis:

In this study, three versions of the YOLO (You Only Look Once) object detection models—YOLOv5, YOLOv8, and YOLOv11—were employed to analyze basketball shot trajectories and predict whether a shot would successfully enter the basket. To evaluate the effectiveness and efficiency of each model, several key performance metrics were considered: **accuracy**, **execution time**, and **runtime**. These parameters were chosen because they are crucial in real-time sports analytics applications where both speed and precision are essential.

The results demonstrate a progressive improvement in performance with each subsequent version of the YOLO model. YOLOv5 served as the baseline, offering decent accuracy and speed. YOLOv8, with its enhanced architectural optimizations, showed a noticeable increase in accuracy and reduced execution time, making it more suitable for near real-time applications. YOLOv11, the most recent version tested, further improved upon these aspects with a highly efficient backbone and better detection capabilities, enabling smoother trajectory tracking and faster predictions.



5. CONCLUSION

This project highlights the application of advanced object detection algorithms—YOLOv5, YOLOv8, and YOLOv11—for the analysis and prediction of basketball shot outcomes using real-time video input. The core methodology involves detecting the basketball and tracking its trajectory across successive frames using deep learning-based models. By examining the spatial movement patterns and temporal consistency of the ball’s motion, the system is able to predict whether a shot will be successful before it reaches the basket. Among the three models evaluated, YOLOv11 demonstrated the highest accuracy and the fastest inference speed, outperforming YOLOv5 and YOLOv8 in both detection precision and real-time responsiveness. Its superior performance makes it particularly suitable for live game analysis and high-speed feedback systems used in sports analytics [5,13].

To ensure the system's reliability and robustness, a comprehensive dataset of basketball shooting scenarios was curated, encompassing a variety of shooting angles, player motions, and lighting conditions. This dataset was carefully annotated and processed with data augmentation techniques to enhance the model’s generalization ability. Following this, a meticulous training and hyperparameter tuning phase was conducted for each model, enabling optimal prediction accuracy. The result is a scalable, high-performance framework for intelligent sports analysis. This system holds strong potential for practical deployment in training environments, where it can assist coaches and analysts in evaluating player technique, refining shot strategies, and improving overall performance. The combination of cutting-edge computer vision techniques with a focus on sports-specific applications underscores the value of AI in enhancing real-world athletic decision-making [7,6].

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