WEAPON DETECTION USING DEEP LEARNING METHODS

TEAMMATES:

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INTRODUCTION

- The increasing demand for effective weapon detection systems arises from growing security concerns in sensitive environments like airports, schools, and public venues. Traditional methods often fail to meet modern safety requirements, prompting the adoption of automated systems powered by deep learning.

- YOLOv11, with its advanced architecture and attention mechanisms, excels in real-time detection but can struggle with accuracy in complex scenarios. Conversely, Faster R-CNN ensures precise localization through its Region Proposal Network but is hindered by slower inference times.

- This study combines YOLOv11's speed and Faster R-CNN's accuracy in an ensemble approach, delivering a balanced solution that addresses the trade-offs between speed and precision. The proposed model offers a scalable, efficient, reliable weapon detection system suitable for real-world deployment, ensuring enhanced safety in high-risk environments.

PROBLEM STATEMENT

- With rising security concerns and the increasing need for public safety, traditional weapon detection systems fail to address the challenges of modern safety demands. Automated weapon detection systems, leveraging advancements in deep learning and computer vision, promise to enhance safety but face critical limitations. Achieving a balance between speed, accuracy, and computational efficiency remains a pressing challenge for real-time deployment in sensitive environments like airports, schools, and public venues.

- Existing models present trade-offs: YOLOv11 offers rapid detection suitable for real-time applications but occasionally sacrifices precision, especially in complex or low-light conditions. Conversely, Faster R-CNN ensures high accuracy with precise object localization but suffers from slower inference times, making it less effective for immediate-response scenarios.

- The need for a unified solution that combines the strengths of these models while overcoming their limitations is essential for developing robust, scalable, and reliable weapon detection systems for real-world deployment.

PROPOSED SYSTEM

YOLOv11 (You Only Look Once):

- An advanced real-time object detection model designed for speed and efficiency, making it ideal for weapon detection in high-risk environments. Its architecture incorporates advanced convolutional layers and attention mechanisms, enabling rapid identification of small or obscured weapons, such as concealed firearms or knives, even in complex scenarios.

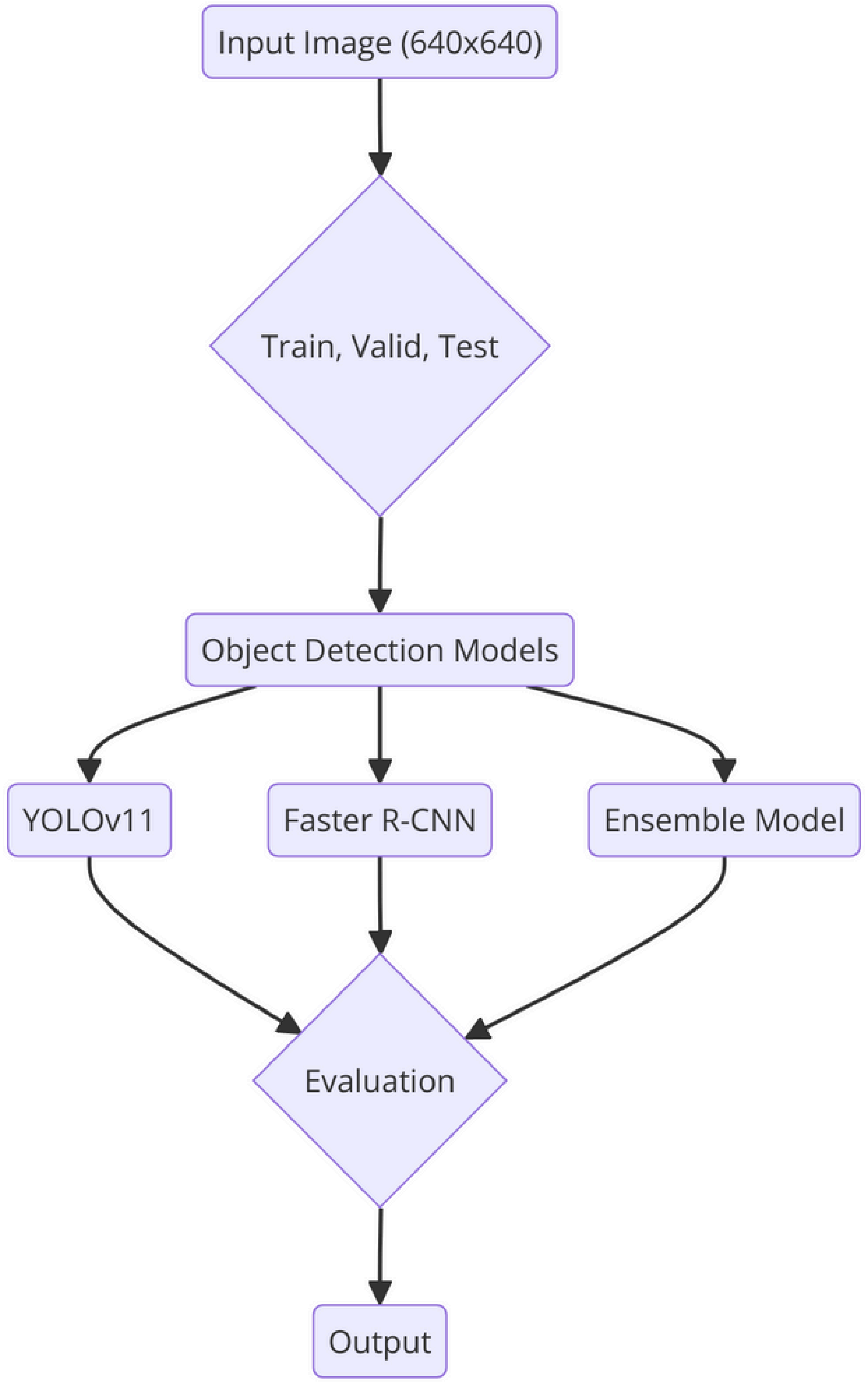
Faster R-CNN:

- A highly accurate object detection model that employs a Region Proposal Network (RPN) for precise localization and bounding box prediction. Its multi-stage process is particularly effective in identifying small or partially visible weapons, ensuring accurate detection even in challenging conditions like poor lighting or cluttered backgrounds.

Ensemble Model:

- By combining YOLOv11's rapid detection capabilities with Faster R-CNN's precision through an ensemble approach, the proposed system addresses the trade-offs between speed and accuracy, offering a robust solution for weapon detection in real-world scenarios.

PROPOSED SYSTEM



YOLOV11

- Overview: YOLOv11 is a real-time object detection algorithm optimized for speed and accuracy. It processes images in a single forward pass, making it highly efficient for scenarios requiring rapid detections. Building on previous YOLO versions, YOLOv11 incorporates advanced features to enhance performance.

- Application: Perfectly suited for weapon detection in surveillance footage, YOLOv11 excels in identifying multiple object types simultaneously, such as firearms and knives, making it ideal for real-time security applications.

- Key Features: YOLOv11 features an improved network architecture for precise object localization, attention mechanisms for handling complex scenes, and support for varying model sizes (e.g., yolo11m.pt), ensuring adaptability to different computational environments.

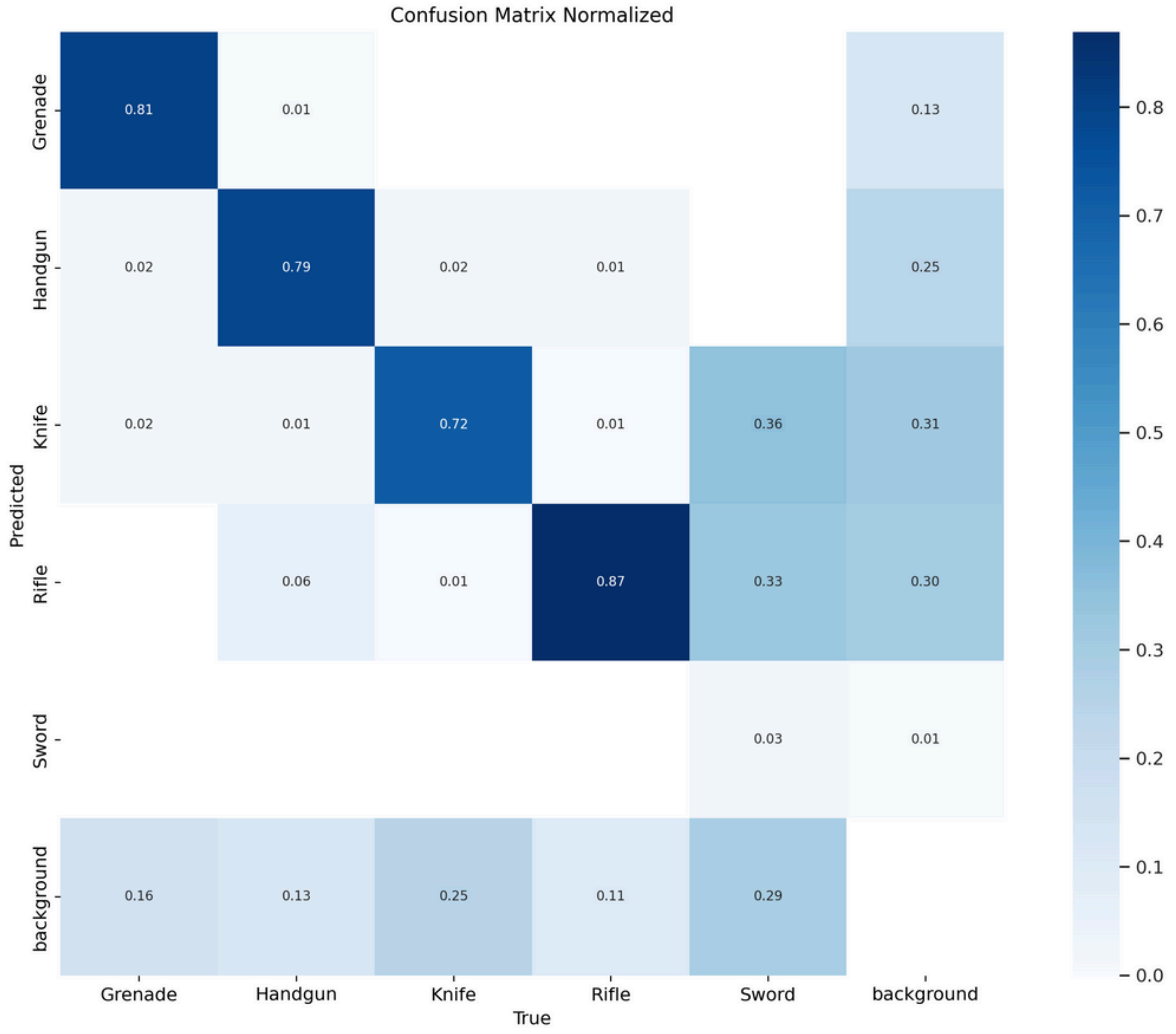
FASTER R-CNN (REGION-BASED CONVOLUTIONAL NEURAL NETWORK)

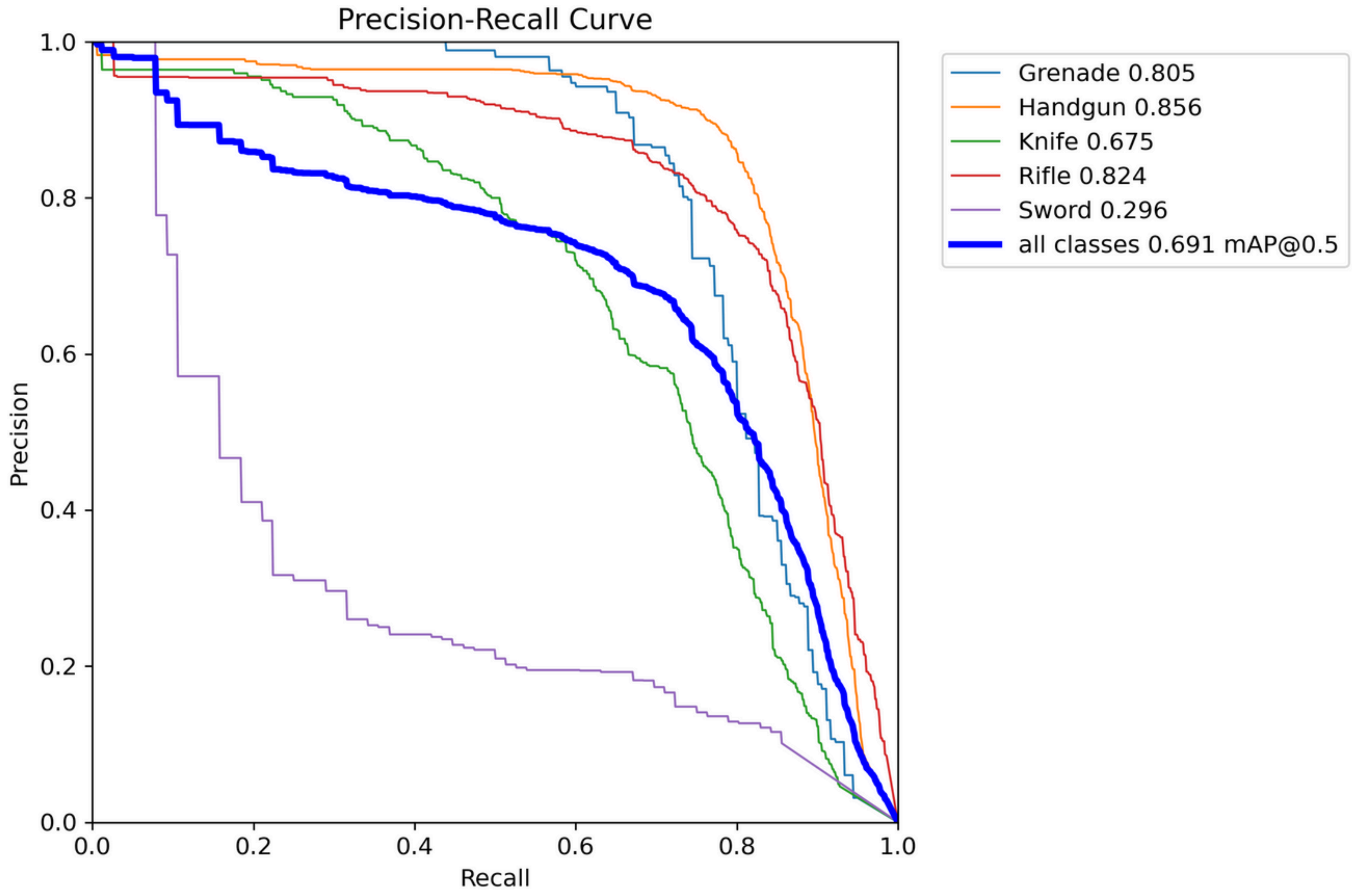
- Overview: Faster R-CNN is a region-based convolutional neural network renowned for its high detection accuracy. It uses a multi-stage pipeline with a Region Proposal Network (RPN) to generate candidate regions, ensuring precise object detection.

- Application: Effective in identifying concealed or partially visible weapons in surveillance footage, Faster R-CNN is ideal for scenarios prioritizing accuracy over speed.

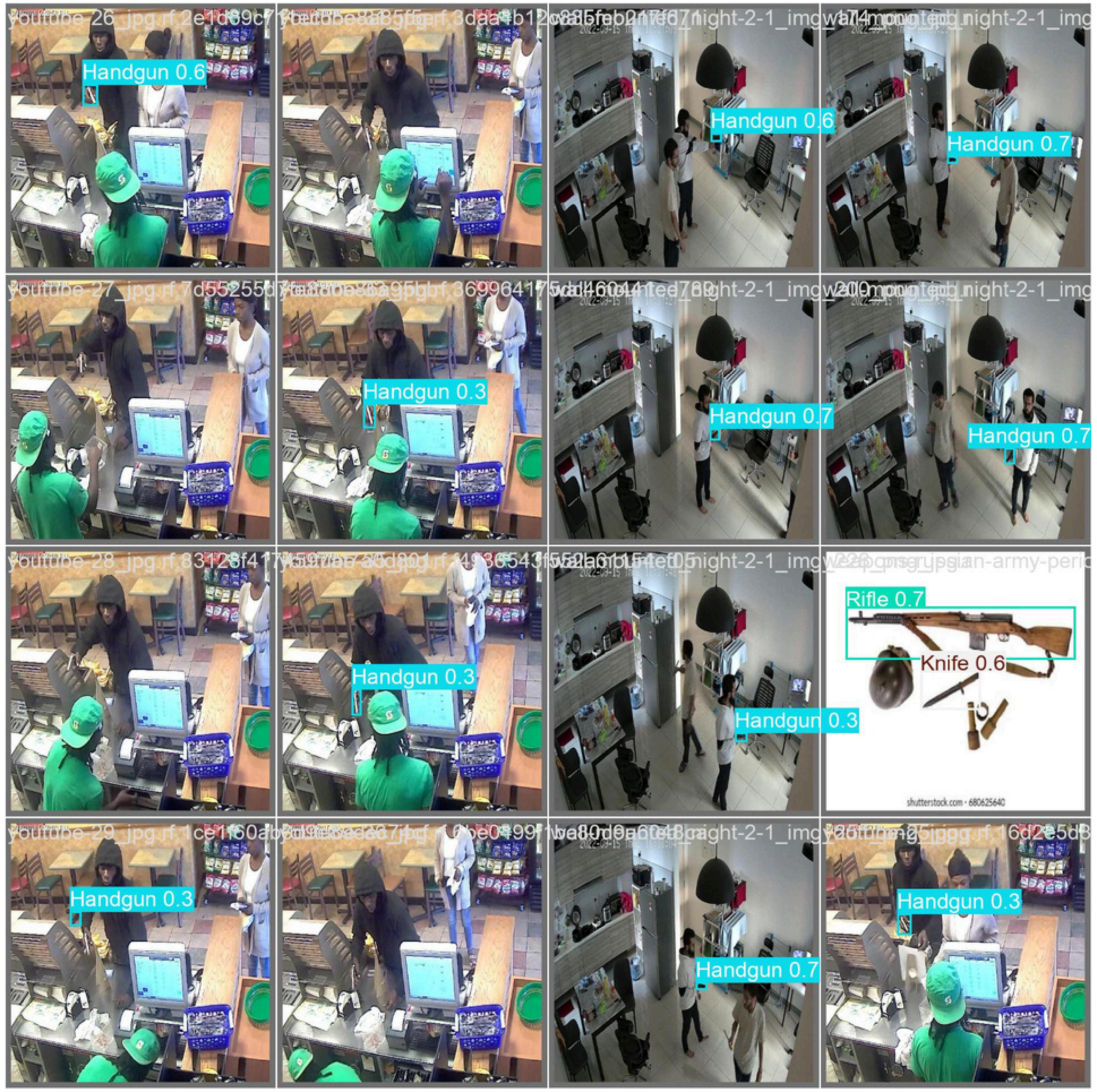
- Key Features: Faster R-CNN employs a robust processing pipeline for accurate bounding box predictions and excels in challenging conditions such as low-light or cluttered environments, offering reliable performance for detecting critical objects.

YOLOV11

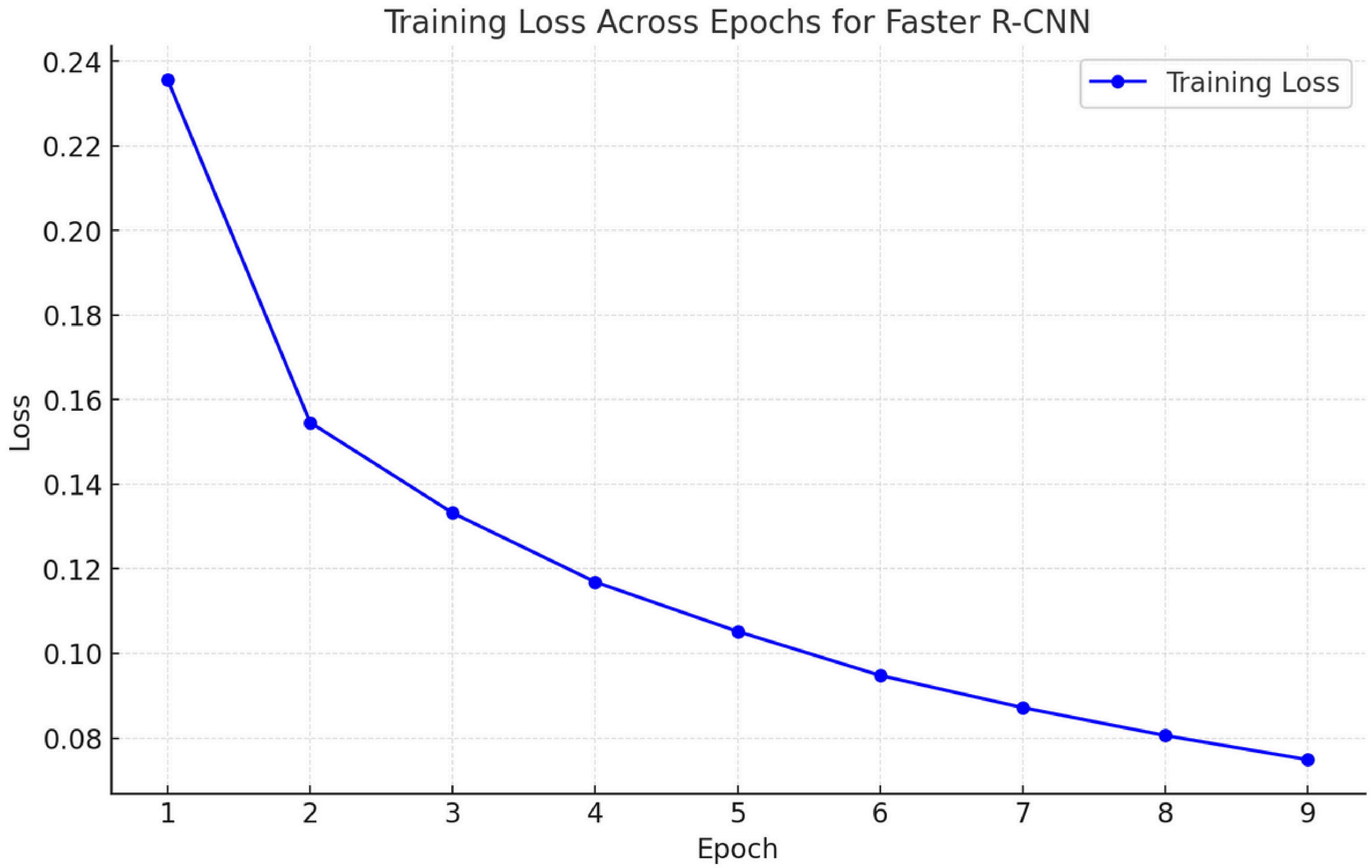

Confusion Matrix Normalized
Predicted
True
Grenade
Handgun
Knife
Rifle
Sword
background
0.81 0.01 0.13
0.02 0.79 0.02 0.01 0.25
0.02 0.01 0.72 0.01 0.36 0.31
0.06 0.01 0.87 0.33 0.30
0.03 0.01
0.16 0.13 0.25 0.11 0.29


Precision-Recall Curve
Precision
Recall
Grenade 0.805
Handgun 0.856
Knife 0.675
Rifle 0.824
Sword 0.296
all classes 0.691 mAP@0.5

YOLOV11 PREDICTIONS

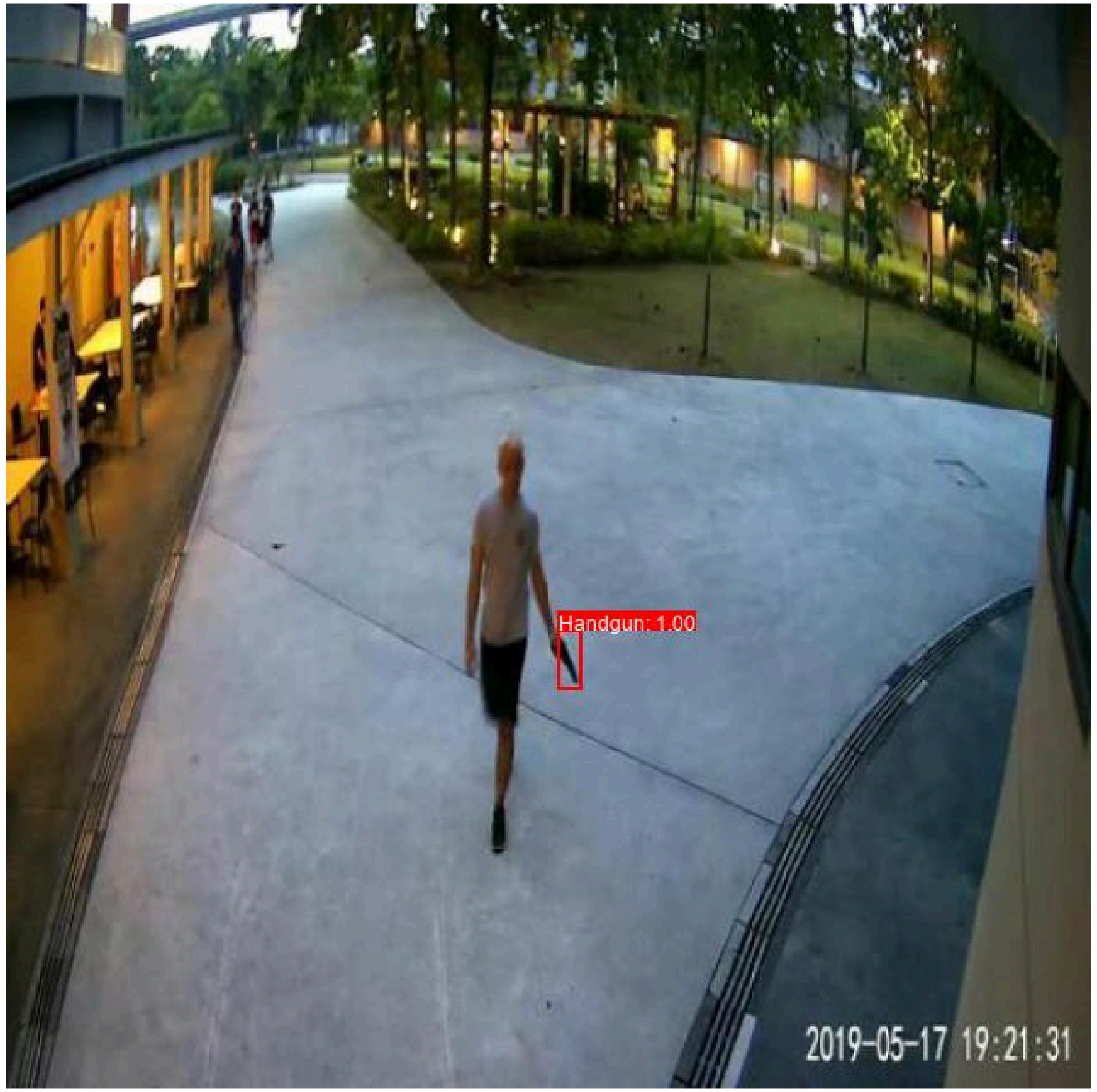


FASTER R-CNN



Training Loss Across Epochs for Faster R-CNN
Training Loss
Loss
0.24
0.22
0.20
0.18
0.16
0.14
0.12
0.10
0.08
1
2
3
4
5
6
7
8
9
Epoch

FASTER R-CNN PREDICTIONS



ENSEMBLE MODEL

Overview:

- The ensemble model combines YOLOv11's speed and Faster R-CNN's accuracy to provide an optimized weapon detection system. YOLOv11 excels in real-time detection, while Faster R-CNN ensures high-precision localization of small or partially visible weapons, making the system ideal for real-world security applications.

Key Features:

- Efficient detection of concealed or small weapons in complex environments.
- Balances speed and accuracy for real-time applications.
- Merges predictions from both models using a weighted voting mechanism to enhance overall performance.

Implementation:

- **Data Preparation:** Used diverse real-world datasets, including CCTV footage and synthetic weapon imagery, for training and testing.
- **Training:** Combined predictions from YOLOv11 and Faster R-CNN models using weighted voting.
- **Evaluation:** Achieved superior metrics, including high mAP and improved F1 scores.

Results:

- The ensemble approach outperformed individual models, providing both rapid detection and high precision, ensuring a reliable and efficient solution for weapon detection in sensitive environments.

Impact:

- A robust solution for real-time weapon detection, enhancing security in airports, schools, and public venues, while addressing the trade-off between speed and accuracy in critical scenarios.

ENSEMBLE MODEL SAMPLE PREDICTIONS

CONCLUSiON AND FUTURE WORK

Conclusion:

- This study evaluated three weapon detection methodologies—YOLOv11, Faster R-CNN, and an ensemble approach combining both models. YOLOv11 demonstrated exceptional speed, making it ideal for real-time applications, while Faster R-CNN excelled in detection accuracy, especially for small or partially visible weapons. The ensemble approach successfully integrated the strengths of both models, achieving a balanced solution that improved accuracy and reduced inference time, making it well-suited for real-world weapon detection challenges. The findings highlight the importance of selecting and combining models based on application-specific needs to address critical trade-offs between speed and precision.

CONCLUSION AND FUTURE WORK

Future Work:

- Data Enhancement: Leverage advanced data augmentation techniques and Generative Adversarial Networks (GANs) to create synthetic datasets, improving model robustness and performance.
- Hybrid Models: Further explore the integration of YOLOv11's speed with the precision of ensemble models for enhanced real-time weapon detection.
- Adaptive Ensembles: Investigate adaptive ensemble approaches that dynamically prioritize models based on the complexity of the detection scene or environmental conditions.
- Model Optimization: Apply model pruning and quantization techniques to optimize the detection system for faster real-time deployment with reduced computational requirements.

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