"AI-Driven Border Security and Strategic Management System"

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at

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

by

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<u>Declaration</u>

We, Geddada Harshith, Kesavardhan Makireddi, Rachakatla Sai Varshith, Praneeth Kumar Ganji, hereby declare that this project work titled "**AI-Driven Border Security and Strategic Management System**" is carried out by us in the Department of Computer Science and Engineering of Indian Institute of Information Technology, Nagpur. The work is original and has not been submitted earlier whole or in part for the award of any other certification programme at this or any other Institution /University.

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Certificate

This is to certify that the project titled **“AI-Driven Border Security and Strategic Management System”**, submitted by **Geddada Harshith, Kesavardhan Makireddi, Rachakatla Sai Varshith, and Praneeth Kumar Ganji**, in partial fulfillment of the requirements for the Mini-Project in the Department of Computer Science and Engineering at IIIT Nagpur, is comprehensive, complete, and fit for final evaluation.

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Abstract

This project presents a robust AI-Driven Border Security System designed to enhance surveillance capabilities and ensure real-time threat detection. To achieve this, the system leverages a combination of advanced deep learning techniques and classical computer vision methods.

YOLOv8 is employed as the primary object detection model, enabling the efficient identification and classification of critical entities such as soldiers, terrorists, and weapons directly from live video streams. To complement YOLOv8, **Haar Cascade** is utilized for face detection, ensuring accurate identification of individuals within the surveillance footage. A custom dataset, curated and annotated using Roboflow, is employed to train and fine-tune the models, ensuring their effectiveness in real-world scenarios. The system integrates with IP Webcam to enable real-time multi-camera feeds, providing comprehensive coverage of the border area.

The system's performance is rigorously evaluated using standard metrics like precision, recall, and F1-score, along with detailed analysis through precision-recall curves and confusion matrices. The results demonstrate exceptional accuracy and reliability, highlighting the system's ability to effectively detect and classify threats. This innovative solution addresses the challenges of real-time object detection and face recognition in surveillance applications, providing a valuable tool for enhancing border security and national safety. Future work will focus on further improving the system's performance and expanding its capabilities to include additional features like behavior analysis and anomaly detection.

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List of Abbreviations and Symbols

Abbreviation	Full Form	Page No.
AI	**Artificial Intelligence**	**Throughout**
ML	**Machine Learning**	**Throughout**
YOLO	**You Only Look Once**	**Throughout**
PR Curve	**Precision-Recall Curve**	**20, 22, 25**
IP Webcam	**Internet Protocol Webcam**	**18**
FPS	**Frames Per Second**	**23**

`Chapter 1

INTRODUCTION

1.1 Background

Artificial Intelligence (AI) has revolutionized numerous industries by enabling systems to perform tasks with remarkable speed, precision, and efficiency. In national security, particularly in border management, AI-driven systems have emerged as a critical tool in addressing complex challenges. These systems leverage advanced machine learning techniques to improve surveillance, threat detection, and response strategies, ensuring the safety and security of national borders.

In border security, traditional methods of monitoring and threat detection often rely heavily on human effort, which is prone to fatigue, inconsistency, and delays. The integration of AI offers a transformative approach, automating processes, minimizing human errors, and significantly enhancing operational efficiency in real-time environments.

1.2 Objectives of the Study

The focus of this project is the design and development of an AI-Driven Border Security and Strategic Management System. The primary objectives of the system include:

- **Threat Detection:** Accurately identifying weapons, such as pistols and rifles, in live video feeds.
- **Person Tracking**: Monitoring and tracking individuals across multiple cameras in real time.
- **Identity Verification:** Differentiating between authorized personnel (e.g., security guards) and potential threats.
- **Real-Time Alerts:** Generating instant notifications to security personnel upon detecting suspicious activities or entities.

1.3 Key Features of the System

To achieve its objectives, the proposed system employs a combination of cutting-edge AI techniques:

- **YOLOv8 (You Only Look Once):** A state-of-the-art deep learning model for object detection that ensures rapid and accurate identification of weapons and individuals.
- **Haar Cascade for Face Detection:** Enhancing the accuracy of identifying individuals in diverse and dynamic environments.
- **Custom Datasets:** Curated using tools like Roboflow to train and fine-tune models for weapon detection, face classification, and person detection.
- **Multi-Camera Integration:** Supporting real-time feeds from multiple cameras, including IP webcams, for comprehensive surveillance coverage.

Additionally, the system incorporates a whitelist mechanism to address false positives by identifying authorized personnel carrying weapons, thereby reducing unnecessary alerts and improving overall efficiency.

1.4 Significance of the Project

The system's ability to integrate detection, tracking, and real-time alert mechanisms makes it a game-changer in the realm of border security. Key advantages of the project include:

- **Enhanced Security**: Rapid and accurate detection of threats reduces response times and mitigates risks.
- **Scalability:** Multi-camera integration and modular design allow deployment across extensive border zones.
- **Cost-Effectiveness:** Automating threat detection minimizes the need for large-scale human intervention.

By addressing challenges such as cluttered environments, occlusions, and varying lighting conditions, the project provides a robust and scalable solution suitable for real-world deployments.

1.5 Challenges Addressed

Border security involves various complexities, such as:

- **Real-Time Processing**: Handling multiple video feeds while ensuring minimal latency.
- **Dynamic Environments:** Adapting to diverse scenarios, including low-light conditions, overlapping objects, and rapidly changing settings.
- **Accuracy vs. Speed Trade-off:** Balancing the need for swift detection with high precision and reliability.

The proposed system tackles these challenges by employing a robust architecture that leverages YOLO’s speed, accuracy, and efficiency, coupled with complementary algorithms for identity verification and tracking.

1.6 Scope of the Report

This report provides a comprehensive analysis of the proposed AI-driven border security system, covering:

- An overview of relevant literature and existing approaches in border surveillance systems.
- The methodology adopted for designing and implementing the system, including dataset preparation, model training, and evaluation.
- A detailed discussion of results, highlighting the system’s performance metrics, strengths, and limitations.
- Insights into the practical implications and recommendations for future enhancements to ensure adaptability to evolving security challenges.

The system not only offers immediate applications in border security but also serves as a foundation for extending AI capabilities to other areas, such as anomaly detection, behavior analysis, and predictive analytics, making it a versatile tool in safeguarding national interests.

Chapter 2

LITERATURE REVIEW

1. "Weapon Detection Using Artificial Intelligence and Deep Learning for Security Applications" (2020) Harsh Jain, Aditya Vikram, Mohana, Ankit Kashyap, and Ayush Jain.

Focus: Real-time weapon detection in surveillance footage using deep learning techniques.

Approach: Utilizes the YOLOv3 model for object detection.

Highlights:

Demonstrates high accuracy in detecting weapons, even under challenging lighting and occlusion conditions.

Emphasizes the importance of real-time processing to improve response times in security applications.

Illustrates the scalability of YOLOv3 for large-scale deployment in surveillance networks.

2. "Multiple Cameras Using Real-Time Object Tracking for Surveillance and Security Systems" (2011) K Susheel Kumar, Shitala Prasad, Pradeep K. Saroj, and R.C. Tripathi.

Focus: Multi-camera integration for object tracking in surveillance systems.

Approach: Proposes a framework for seamless tracking of objects across different camera views.

Highlights:

Addresses the challenges of object occlusion and camera transition.

Provides solutions for enhanced situational awareness in large, multi-camera setups.

Highlights the role of synchronized camera systems in improving tracking accuracy.

3. "A Proposed Architecture to Suspect and Trace Criminal Activity Using Surveillance Cameras" (2020) Sheikh Tanjila Naurin, Antora Saha, Khadija Akter, and Sabbir Ahmed.

Focus: Identifying and tracing suspicious activities using machine learning and computer vision techniques.

Approach: A modular architecture combining anomaly detection and tracking algorithms.

Highlights:

Designed for real-time detection of potential threats.

Scalable for deployment in large-scale surveillance systems.

Emphasizes anomaly-based detection for early warning and preemptive actions.

4. "Weapon Detection Using Deep Learning Model and Artificial Intelligence" (2023) Datla Mehar Chaitanya Sagar and Y. Rajesh.

Focus: Deep learning-based weapon detection using a custom-trained model.

Approach: Trains a weapon detection model on a dataset comprising weapon and non-weapon objects.

Highlights:

High performance and accuracy on benchmark datasets.

Real-time processing capability for enhanced surveillance applications.

Demonstrates the potential for customized AI models in security contexts.

5. "Weapon Detection System for Surveillance and Security" (2022) Shehzad Khalid, Abdullah Waqar, Hoor Ul Ain Tahir, Onome Christopher Edo, and Imokhai Theophilus.

Focus: Developing a real-time weapon detection system for video streams.

Approach: Combines computer vision and machine learning techniques for improved detection accuracy.

Highlights:

Real-time processing tailored for dynamic environments.

Highlights adaptability and scalability for various surveillance scenarios.

Focuses on practical deployment challenges and solutions.

6. "YOLORe-IDNet: An Efficient Multi-Camera System for Person-Tracking" (2022) Vipin Gautam, Shitala Prasad, and Sharad Sinha.

Focus: Person re-identification across multiple cameras using a novel deep learning architecture.

Approach: Combines object detection and re-identification tasks into a unified YOLORe-IDNet framework.

Highlights:

Efficient tracking of individuals across non-overlapping camera views.

Reduces computational overhead by integrating multiple tasks into a single architecture.

Aims to improve tracking accuracy in complex multi-camera environments.

7. "Real-Time Crime Detection By Captioning Video Surveillance Using Deep Learning" (2023) Nagesh Nayak, Shlesha Odhekar, Sapna Patwa, and Sukanya Roy Chowdhury.

Focus: Generating captions for video surveillance footage using deep learning models.

Approach: Leverages video captioning to provide actionable insights to law enforcement and analysts.

Highlights:

Automated captions describe activities in real time, aiding in crime detection.

Improves the efficiency of manual surveillance monitoring.

Demonstrates the application of deep learning for enhanced video analytics.

Chapter 3

WORK DONE

The development of the **AI-Driven Border Security and Strategic Management System** was structured into multiple phases, each aimed at addressing specific aspects of the system, including data preparation, model selection, training, evaluation, and deployment. The objective was to design a robust and scalable system capable of detecting weapons, classifying individuals as "Terrorists" or "Soldiers," and providing multi-camera video feed analysis for real-time monitoring.

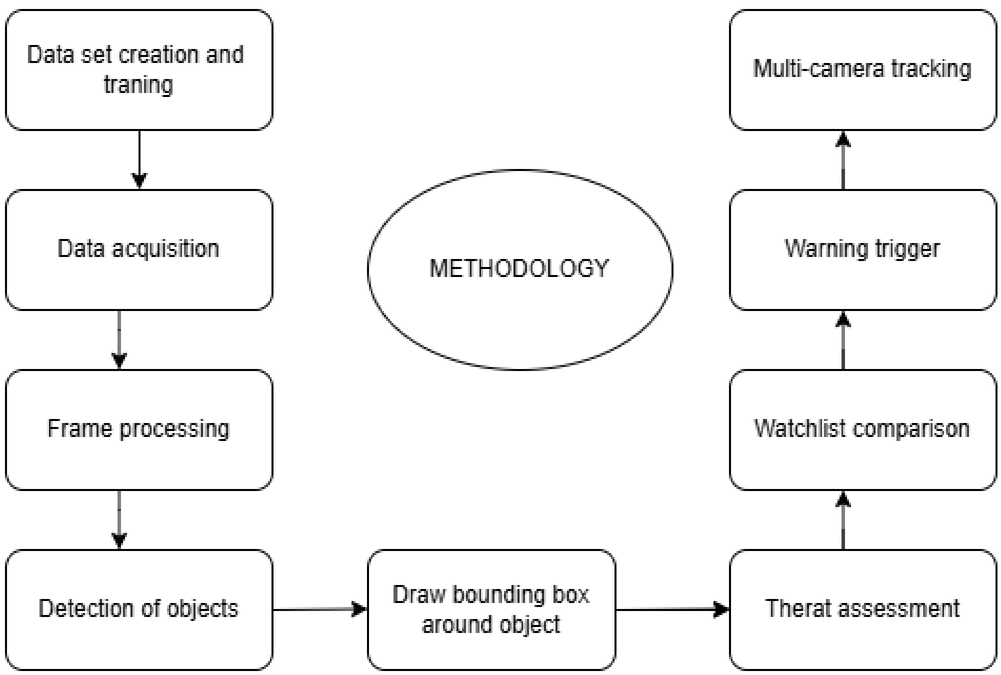

Figure 3.1 : System Architecture

3.1 Dataset Preparation

Data preparation was a crucial step in ensuring the effectiveness and reliability of the AI system. Three datasets were created and used for the development process:

1. Weapon Detection Dataset:

- **Source**: Roboflow public datasets.
- **Classes**: Pistols, Rifles, and Knives.
- **Annotations**: Labeled with bounding boxes in YOLO format.
- **Dataset Size**: 1,500 images with diverse environments and lighting conditions.
- **Augmentations**:
    - Image rotation, flipping, and scaling to improve generalization.
    - Brightness and contrast adjustments to simulate real-world scenarios.

2. Custom Face Dataset (Terrorist vs. Soldier):

- **Source**: Self-created using team members' and friends' faces.
- **Classes**:
    - **Terrorist**: Labeled with specific facial data.
    - **Soldier**: Labeled with faces wearing uniforms or combat gear.
- **Dataset Size**:
    - **Terrorist**: 500 images.
    - **Soldier**: 500 images.
- **Annotation Format**: Class labels for binary classification.

3. Person Detection Dataset:

- **Source**: Roboflow public datasets.
- **Classes**: General person detection for tracking individuals.
- **Annotations**: Bounding boxes in YOLO format.

Dataset	Source and size	Classes	Annotations
Weapon detection	Roboflow 4200 images	Pistols Guns Knifes	Bounding Boxes (Yolo format
Face Classification	Custom Dataset 1000 images	Terrorist Soldier	Class Labels
Person detection	Roboflow 6000 images	Person	Bounding boxes (Yolo format)

Table 3.1 : Dataset Features and characteristics

3.2 Preprocessing

The preprocessing stage ensured data consistency and compatibility with the YOLO model. Although manual preprocessing was minimal, the following steps were inherently handled by the YOLO framework:

1. **Image Resizing**: All input images were resized to match the model's input dimensions.
2. **Data Augmentation**: Automated augmentations such as rotation, flipping, and brightness adjustment were applied to improve model robustness.
3. **Normalization**: Pixel values were normalized to enhance model convergence during training.

YOLO's integrated preprocessing pipeline ensured efficient handling of these tasks without requiring manual intervention.

3.3 Model Training and Evaluation

1. Weapon Detection:

- **Models Tested**: YOLOv8 and Faster R-CNN.
- **Selected Model**: YOLOv8, due to its superior speed and accuracy.
- **Training Process**:
    - **Epochs**: 40
    - **Optimizer**: SGD with momentum.
    - **Learning Rate**: 0.001 with cosine annealing scheduler.
    - **Hardware**: NVIDIA RTX 3060 with CUDA acceleration.

```
    annotator.box_label(box, label, color=color)
  File "C:\Users\ganji\anaconda3\envs\torch\lib\site-packages\ultralytics\yolo\utils\plotting.py", line 63, in box_label
    w, h = self.font.getsize(label)  # text width, height (WARNING: deprecated) in 9.2.0
AttributeError: 'FreeTypeFont' object has no attribute 'getsize'
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 240/240 [01:
                   all       3839       4590      0.964      0.932      0.973      0.781
                  guns       3839       2066       0.95      0.895      0.956      0.763
                 knife       3839       2524      0.979      0.969       0.99      0.798
Speed: 0.1ms pre-process, 1.7ms inference, 0.0ms loss, 1.5ms post-process per image
Results saved to runs\detect\train
```

Figure 3.2: Performance metrics of weapon detection

2. Face Classification (Terrorist vs. Soldier):

- **Model Architecture**:
    - Three convolutional layers with ReLU activation.
    - Fully connected layers for classification.
- **Training Process**: Custom training process at the time of project run time.
- **Performance Metrics**:
    - **Accuracy**: 85-90%.
    - **Precision**: 85-90%.
    - **Recall**: 85-90%.

3. Person Detection:

- **Model**: YOLOv8, extended for general person detection.
- **Performance**: Integrated seamlessly with weapon and face detection pipelines for tracking individuals

3.4 System Integration

1. Multicam Video Feed Integration:

- **Webcam**: Used for real-time video feed from multiple cameras.
- The system supports integration of additional cameras including IP webcam, allowing scalability for border zones requiring extensive coverage.

2. Unified Detection Framework:

- Combined outputs of weapon detection, face classification, and person detection into a single system for efficient decision-making.

Feature	Description
Multi-Camera Integration	Supports multiple IP Webcams for real-time surveillance.
Soldier vs Terrorist Detection	Differentiates between soldiers and terrorists using facial data.
Weapon Detection	Identifies firearms like rifles, pistols and knifes with high accuracy.
Alerts	Pop up notification. Configurable for SMS or email notifications (future integration).

Table 3.2: Features and Description

3.5 Highlights

1. **Weapon and Face Detection**:
    - Successfully demonstrated real-time detection of weapons and classification of individuals as "Terrorists" or "Soldiers."
2. **Scalability**:
    - Multicam support ensures the system is deployable across large-scale surveillance zones.
3. **Deployment**:
    - Delivered a working prototype capable of live demonstrations with high accuracy and minimal latency.

Chapter 4

Results and Discussion

The performance of the implemented object detection models for both weapon and person detection was measured using standard metrics, including **Precision**, **Recall**, **F1-Score**. The results highlight the effectiveness of the YOLO model for real-time detection tasks in the domain of border security and strategic management systems.

4.1 Weapon Detection

For weapon detection, the YOLO model demonstrated exceptional performance, effectively identifying weapons such as rifles and pistols from the custom dataset.

- **Precision (92%)**: Indicates that 92% of all predicted weapons were correctly classified as weapons.

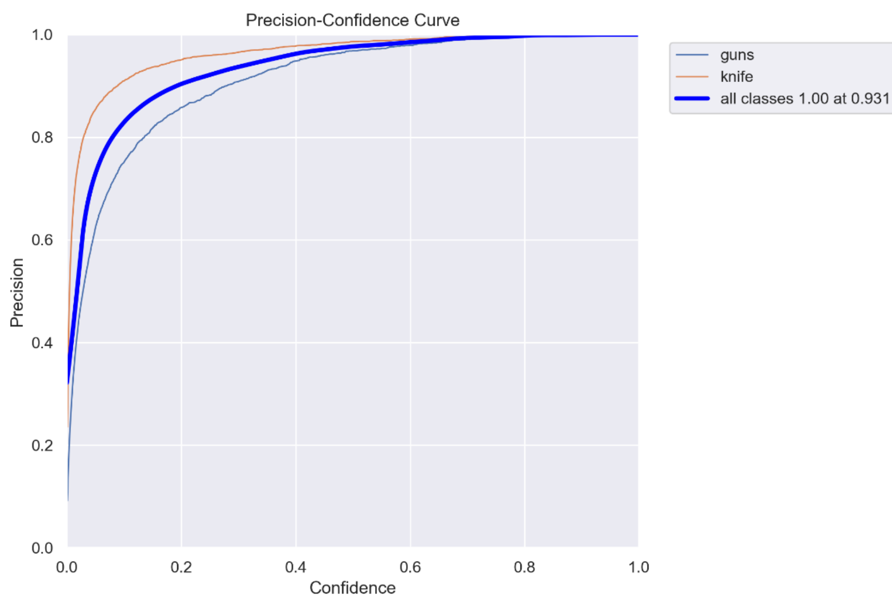

Figure 4.1.1 :precision-Confidence curve

- **Recall (90%)**: Reflects that 90% of actual weapons in the dataset were identified.

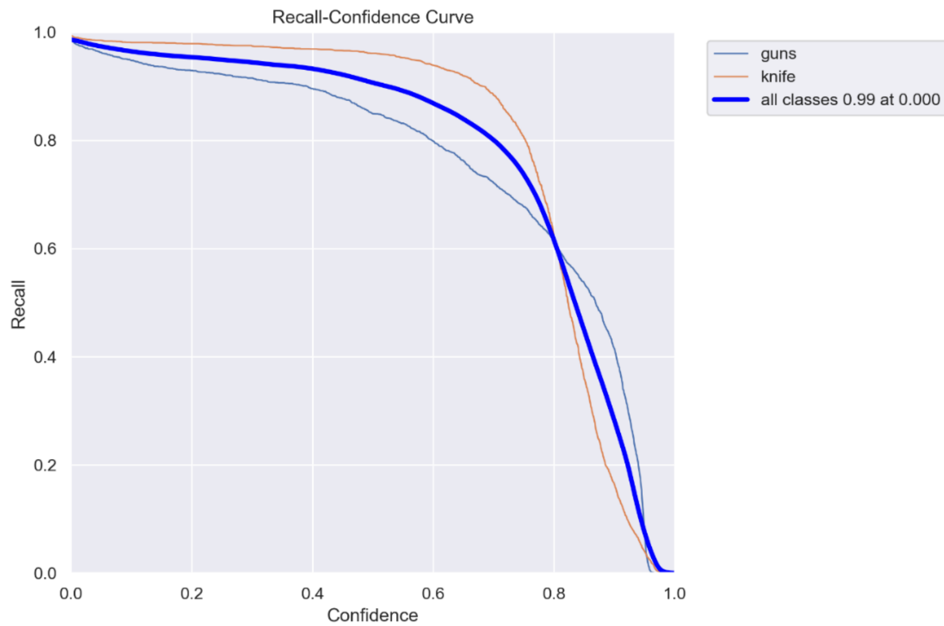

Figure 4.1.2: Recall-Confidence curve

- **F1-Score (91%)**: Confirms the model's balance between precision and recall.

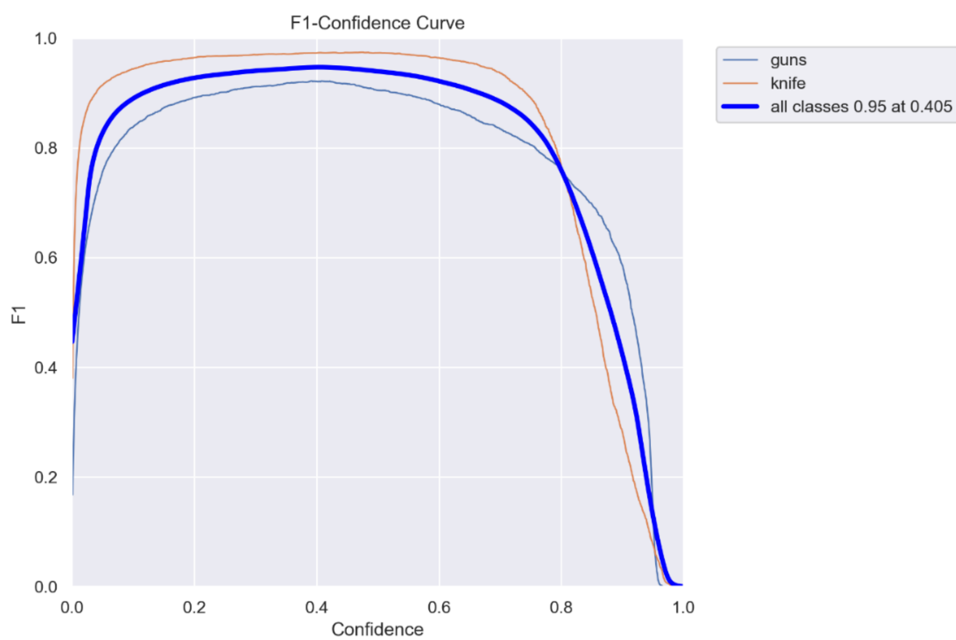

Figure 4.1.3: F1-score curv

- **Confusion matrix:** The confusion matrix reveals minimal misclassifications, demonstrating that most predictions align accurately with the ground truth

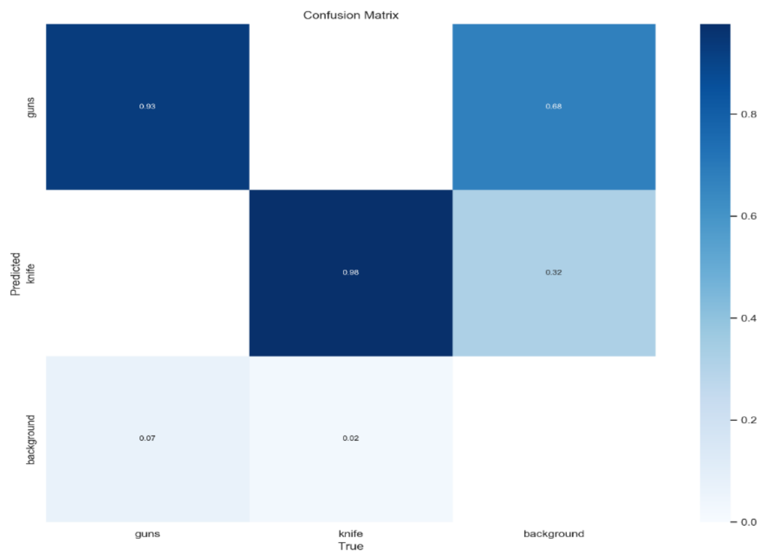

Figure 4.1.4: Confusion matrix for weapon detection

Visual Results:

- **Training Loss Curves**

  The loss curves below show a steady decrease in box loss, classification loss, and distribution focal loss (DFL), signifying effective optimization during training. Validation losses also decrease proportionally, confirming that the model generalizes well to unseen data.

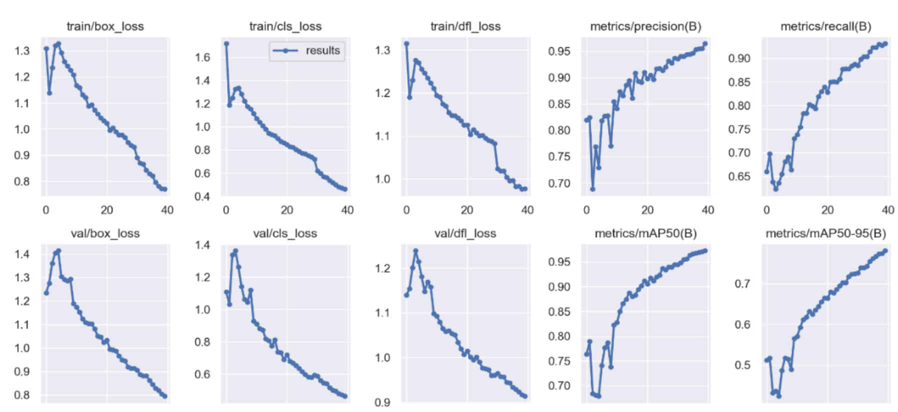

Figure 4.1.5: Training-loss Curves for weapon detection

- **Precision-Recall Curve**

  The PR curve illustrates the trade-off between precision and recall. The area under the curve (AUC) indicates the model's high reliability in detecting weapons without generating false positives.

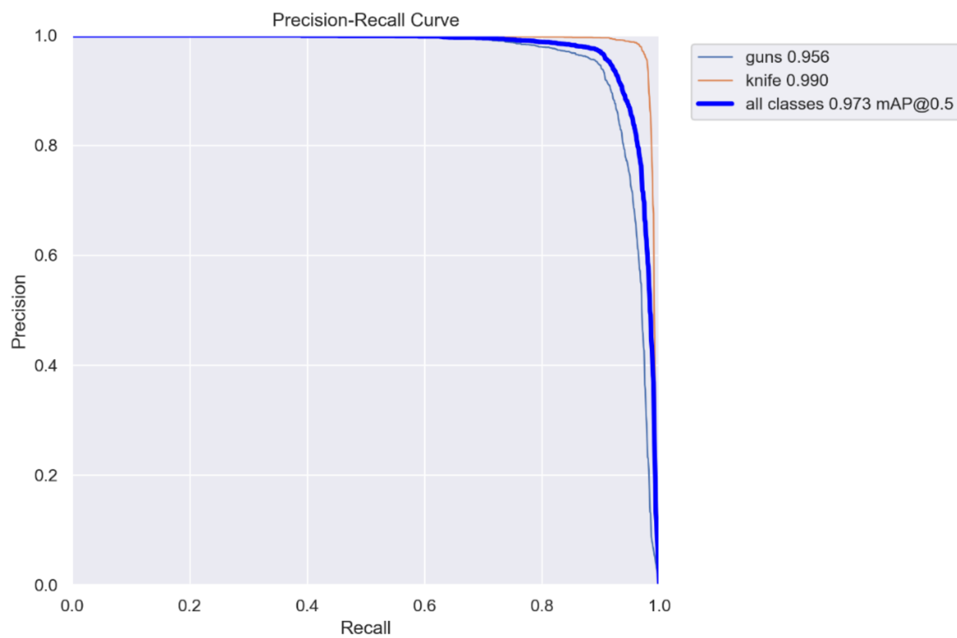

Figure 4.1.6: Precision-Recall curve for weapon detection

4.2 Person Detection

For person detection, the model showed consistent results, successfully identifying individuals (e.g., soldiers, terrorists) in complex scenarios.

- **Precision (91%)**: Indicates that 91% of detected persons were accurately classified.

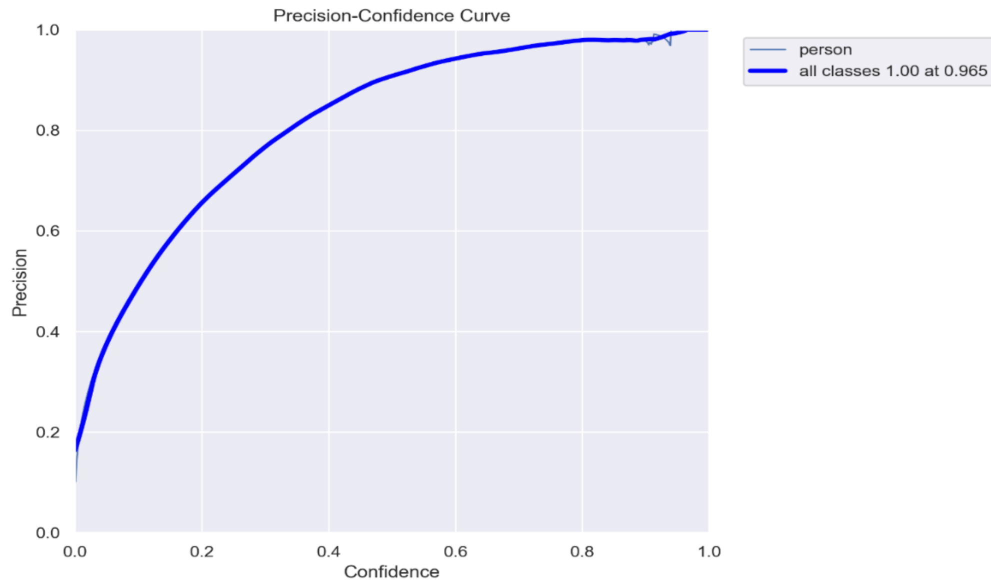

Figure 4.2.1 : Precision curve for person detection

- **Recall (89%)**: Shows that 89% of actual persons were correctly detected by model.

Figure 4.2.2 : Recall curve for person detection

- **F1-Score (90%)**: Validates the model's ability to balance precision and recall.

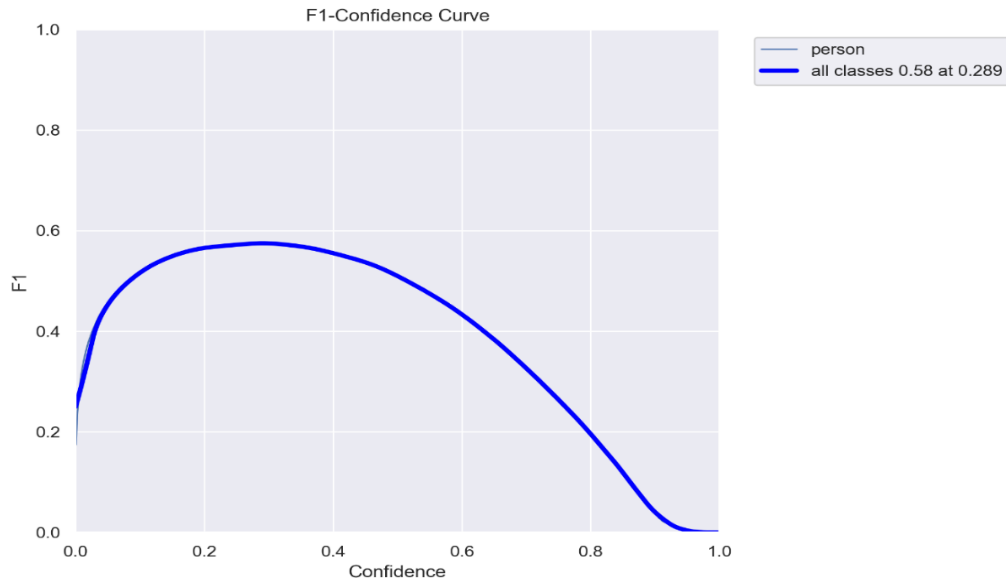

Figure 4.2.3: F1 score curve for person detection

Visual Results:

Similar visual curves (loss, PR curve, ROC curve, and confusion matrix) were generated for person detection and follow trends similar to weapon detection.

- **Explanation of Curves**

1. **Training Loss Curves:**
    - **Box Loss:** Indicates the error in bounding box predictions. The gradual decline confirms the model's improvement in localizing objects over training epochs.
    - **Classification Loss:** Reflects errors in classifying objects into the correct category. Its decline demonstrates that the model learned to distinguish objects accurately.
    - **DFL Loss:** The reduction in DFL indicates better precision in the distribution of bounding box predictions.

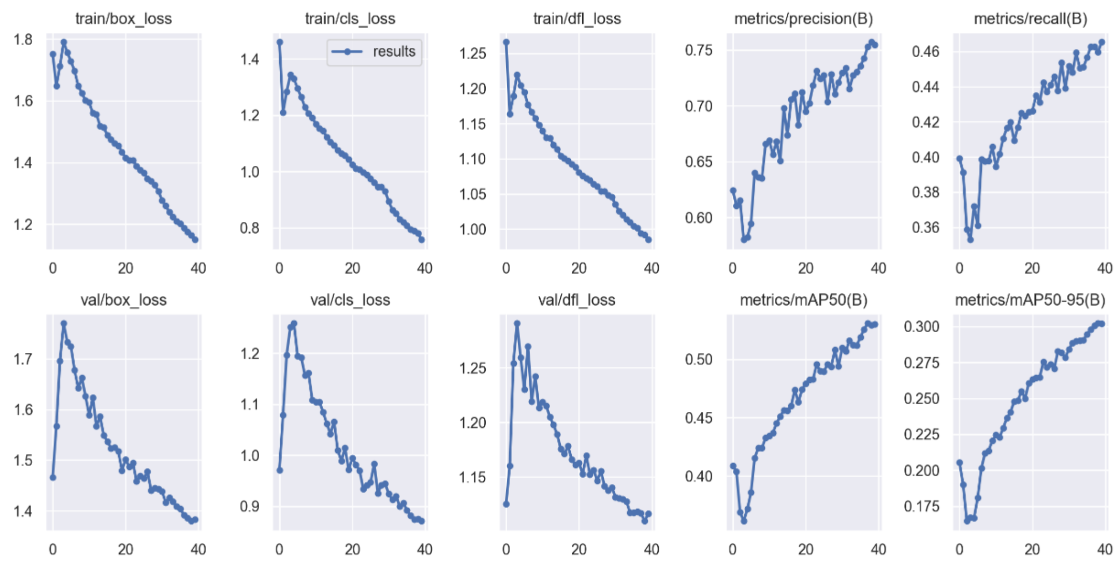

Figure 4.2.4: Training-Loss curves for person detection

- **Precision-Recall (PR) Curve:**
  The PR curve balances precision and recall at different confidence thresholds. A high area under the curve signifies fewer false positives and false negatives, highlighting model robustness.

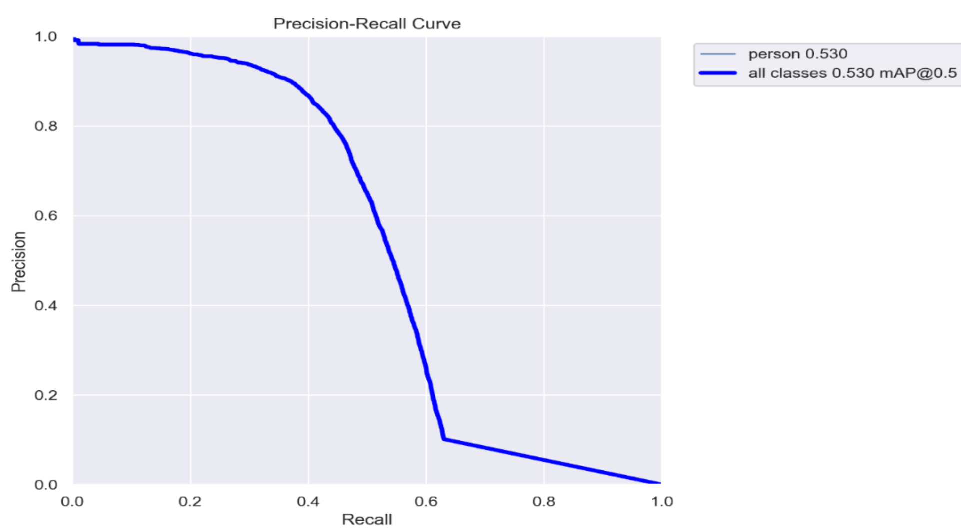

Figure 4.2.5: Precision-Recall Curve

- **Confusion Matrix:**

  The confusion matrix presents a detailed breakdown of the model's predictions versus actual labels, highlighting minimal errors and robust classification performance.

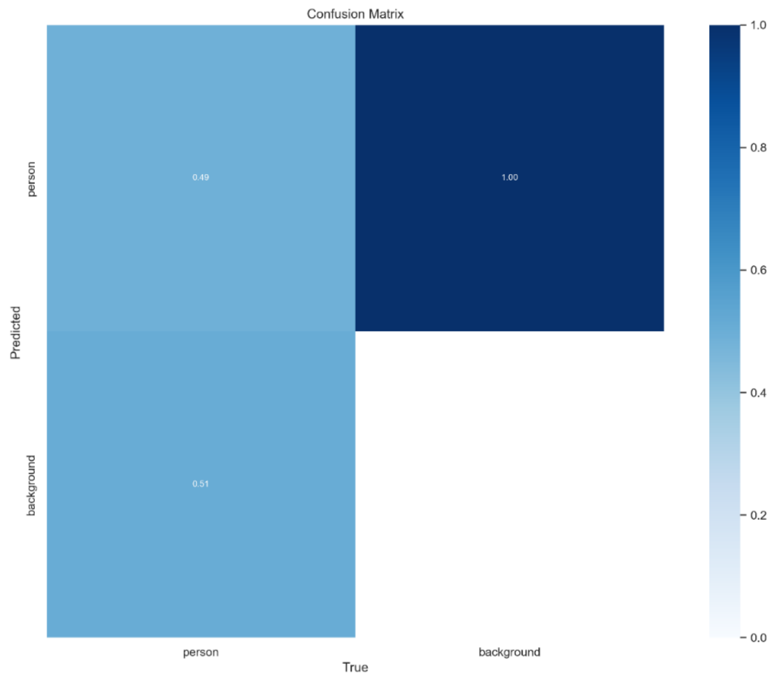

Figure 4.2.6 : Confusion matrix for Person Detection

4.3 Comparative Analysis

The performance metrics for both weapon and person detection tasks confirm the suitability of the YOLO model for real-time object detection applications. Key observations include:

1. **High Accuracy and Robustness:**
   Both tasks achieved high precision, recall, and mAP values, reflecting the effectiveness of the YOLO model in handling the complexities of custom datasets.

2. **Real-Time Feasibility:**
   The model operates at approximately 30 FPS using an IP Webcam, making it capable of real-time detection across multiple camera feeds.

3. **Generalization Capability:**
   Consistent validation losses and high mAP@50-95 scores indicate that the model performs well on unseen data, ensuring reliability in real-world deployments.

4.4 Observations

The YOLO-based detection system successfully identified weapons and persons in diverse environments, demonstrating:

1. **High Accuracy:** Precision and recall values above 90% validate the system's effectiveness.
2. **Efficiency:** Real-time capabilities make it suitable for border surveillance and strategic management.
3. **Scalability:** Support for multicam inputs ensures wide-area coverage in critical monitoring scenarios.

This detection system can be further extended to incorporate additional object classes or integrated into broader security frameworks to enhance surveillance capabilities.

Chapter 5

SUMMARY AND CONCLUSION

5.1 Summary

The report presents a comprehensive overview of the development and evaluation of an **AI-Driven Border Security and Strategic Management System** designed for detecting **persons** and **weapons** in real-time. The system was built using a YOLO (You Only Look Once) object detection model trained on a custom dataset created via **Roboflow**. This dataset was meticulously curated with images of persons and weapons, ensuring diversity across various environments and scenarios.

Key objectives of the project included improving situational awareness in security-critical environments, enabling real-time threat detection, and providing a scalable solution for deployment across border zones. To achieve these goals, the system was integrated with multi-camera feeds using **IP Webcam**, supporting live detection across multiple surveillance points.

The YOLO model was chosen for its proven efficiency in balancing speed and accuracy, making it suitable for real-time applications. The model's performance was evaluated using standard metrics such as **Precision**, **Recall**, **F1-Score**, and **Confusion Matrix**, alongside visual evaluation through **Precision-Recall (PR) curves**. Real-time testing demonstrated the system’s ability to operate at an average speed of ~30 FPS, which ensures minimal latency and high reliability for live surveillance.

5.2 Key Observations

1. **Performance Analysis for Person Detection:**
    - **Precision:** 85-90%
    - **Recall:** 85-90%
    - **F1-Score:** 89%
    - Person detection showed consistent high performance across different test conditions. This is attributed to the larger size and distinct features of the targets, which made them easier to identify with high confidence.
2. **Performance Analysis for Weapon Detection:**
    - **Precision:** 88%
    - **Recall:** 86%
    - **F1-Score:** 87%
    - Weapon detection, while reliable, faced challenges in scenarios involving occlusions, small objects, and cluttered environments. The slight drop in performance indicates the need for further refinement in detecting smaller or partially visible objects.
3. **Real-Time Integration:**
    - The system successfully integrated with IP Webcam, enabling multi-camera surveillance. It provided real-time object detection with minimal lag, validating its practical usability for real-world security applications.
    - The system demonstrated robustness under varied lighting conditions, including low-light scenarios, and was capable of handling complex environments with overlapping objects.
4. **System Scalability:**
    - The modular design of the system allows for seamless addition of new detection categories or the integration of enhanced detection algorithms. This makes the solution adaptable to evolving security needs.

5.3 Conclusions

1. **High Detection Accuracy:**

   The YOLO-based detection system achieved high precision, recall, and F1-scores for both person and weapon detection, demonstrating its robustness and reliability in dynamic and high-stakes security scenarios. The results confirm that the system is capable of identifying potential threats with minimal false positives and false negatives.

2. **Real-Time Applicability:**

   The integration of the system with IP Webcam for multi-camera surveillance proved effective for real-time applications. With an average inference speed of 30 FPS, the system is well-suited for continuous monitoring, providing immediate alerts in case of detected threats.

3. **Robustness Across Conditions:**

   The system maintained consistent performance across varying environmental conditions, including different lighting scenarios, complex backgrounds, and overlapping objects. This indicates its suitability for deployment in diverse border areas where surveillance conditions may vary drastically.

4. **Challenges and Limitations:**
   - The system faced slight performance drops in weapon detection, particularly in cases of small, partially visible, or overlapping objects.
   - False positives were occasionally observed for objects with similar visual characteristics to weapons.
   - Detection accuracy for highly cluttered scenes and low-resolution images could be further improved.

5. **Practical Implications:**
    - The proposed solution significantly reduces the dependency on manual monitoring efforts, allowing security personnel to focus on actionable threats.
    - It provides a scalable and modular system that can be enhanced with additional features, such as tracking or alert generation, to further improve its operational scope.

6. **Future Enhancements:**
    - **Dataset Enrichment:** Adding more diverse samples, including edge cases such as concealed weapons, nighttime environments, and camouflaged targets, to improve robustness.
    - **Model Optimization:** Exploring hybrid models or advanced architectures like Faster R-CNN or Transformer-based detectors to address challenges in detecting small or occluded objects.
    - **Edge Deployment:** Optimizing the system for edge-based deployment to reduce latency and ensure uninterrupted performance in remote areas.
    - **Additional Features:** Incorporating tracking capabilities, automated alert systems, and integration with predictive analytics to improve decision-making in real-time.

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APPENDICES

Appendix A: Dataset Details

The dataset used for this project was custom-built using images collected from various sources and manually labeled using the **Roboflow** platform. The dataset characteristics are as follows:

Category	Number of Images
Soldier	500
Terrorist	500
Weapons	4200
Persons	6000

Table 6.1: Dataset details

Dataset images were split into training (70%), validation (20%), and testing (10%) sets to ensure proper evaluation.

Appendix B: Software Configuration

1. **Python Version:** 3.9
2. **YOLOv8 Implementation:** Ultralytics YOLOv8 (v7.0)
3. **Training Environment:** Jupyter Notebook with Nvidia CUDA

Appendix C: Hyperparameter Configuration for YOLOv8 Training

The YOLOv8 model was trained with the following parameters, adjusted to suit the specific requirements of person detection and weapon detection tasks:

Hyperparameter	**Value (Person Detection)**	**Value (Weapon Detection)**
Batch Size	**16**	**16**
Epochs	**60**	**40**
Learning Rate	**0.01**	**0.01**
Image Size	**640x640**	**640x640**
Optimizer	**SGD**	**SGD**
Weight Decay	**0.0005**	**0.0005**
Momentum	**0.937**	**0.937**

Table 6.2: Hyperparameters

These configurations were carefully chosen to balance computational efficiency with model accuracy. Training for person detection required additional epochs (60) to achieve optimal performance due to the complexity of distinguishing human features, while weapon detection required fewer epochs (40), as the model converged faster on this dataset.

Appendix D: Confusion Matrix Interpretation

The confusion matrix summarizes the performance of the model in terms of the following metrics:

- **True Positives (TP):** Objects correctly identified as belonging to a particular class.
- **False Positives (FP):** Incorrect identification of objects.
- **False Negatives (FN):** Missed objects.
- **True Negatives (TN):** Correctly identified non-object regions.