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# AI POWERED THREAT DETECTION USING SURVEILLANCE CAMERAS

**A Tanmai Harshitha**
Department of CSE
Raghu Engineering College
Dakamarri,Visakhapatnam

**B Priyanka**
Department of CSE
Raghu Engineering College
Dakamarri, Visakhapatnam

**A Srikanya**
Department of CSE
Raghu Engineering College
Dakamarri, Visakhapatnam

**D Harsha Vardhan**
Department of CSE
Raghu Engineering College Dakamarri, Visakhapatnam

**ABSTRACT**

This project proposes an AI-powered threat detection system capable of automatically detecting weapons in real time from CCTV footage, specifically focusing on pistols. Security in modern society is a growing concern, especially for countries aiming to create a safe environment for investors and tourists. While Closed Circuit Television (CCTV) cameras are widely used for surveillance, they still depend on human oversight. This project addresses the need for an automated system capable of detecting illegal activities, specifically weapons, in real-time using CCTV footage. Current deep learning techniques, despite advancements in hardware and software, face challenges such as occlusions, viewing angles, and varied environments. This project proposes a solution utilizing state-of-the-art deep learning algorithms for weapon detection, focusing on pistol detection using a custom dataset created from various sources, including manual collections, YouTube, GitHub, and public databases. Through testing multiple models, YOLOv5 emerged as the most effective with an F1-score of 91% and mean average precision (mAP) of 91.73%.

**Keywords:** Weapon Detection, Deep Learning, Object Detection, Artificial Intelligence, Computer Vision, Real-time Surveillance

## I. INTRODUCTION

The increasing reliance on surveillance cameras for public safety and crime prevention highlights the critical role of artificial intelligence (AI) in enhancing threat detection capabilities. Traditional CCTV systems require continuous monitoring by human operators, which often leads to inefficiencies due to fatigue and limited attention spans. With the advent of advanced AI technologies, surveillance systems can now transition from passive monitoring tools to proactive threat detection mechanisms.

This paper focuses on the implementation of an AI-based threat detection system using surveillance cameras to identify and classify potential dangers, such as the presence of handheld weapons. The system leverages cutting-edge deep learning algorithms, specifically convolutional neural networks (CNNs), to enable real-time detection and classification of threats. By incorporating models such as YOLOv5, the solution addresses critical challenges, including low-resolution video quality, occlusion, and the presence of confusing objects, which are commonly encountered in real-world surveillance scenarios.

This deep learning-based approach is for automatic weapon detection and classification in real-time video streams, specifically targeting pistols and revolvers. The method utilizes pre-trained CNN models, such as Yolov11, and a novel dataset created by collecting weapon images from various sources, including CCTV footage and online repositories. This dataset is manually labelled, pre-processed, and enhanced with image filters to improve performance in low-resolution and low-brightness conditions. The goal is to detect weapons with high accuracy and low false positives, a critical factor for security applications.

The proposed system achieved outstanding performance metrics, including a mean average precision (mAP) of 91.73% and an F1 -score of 91%. This demonstrates its capability to accurately detect threats in various orientations and environments, making it a valuable tool for enhancing public safety and reducing response times to potential incidents.

This paper contributes to the body of knowledge in AI-driven surveillance by providing a scalable, efficient, and reliable framework for threat detection, marking a significant step towards safer and more secure public spaces.

## II. LITERATURE SURVEY

"Real-Time Video-Based Threat Detection Using CNN" by Afeez Adekunle Soladoye, Federal University Oye-Ekiti, *Research Gate*, 2024. This study develops a CNN model for real-time threat detection in video feeds, enhancing security by automating the alert process. It demonstrates the effectiveness of CNN in identifying threats, reducing the need for manual monitoring.

"Automatic Detection of Weapons in Surveillance Cameras Using EfficientNet" by Erssa Arif, Arfan Jaffar, *Tech Science Press*, 2022. This research utilizes EfficientNet and a Bidirectional FPN for weapon detection in surveillance, optimizing computational efficiency. The study shows how the EfficientNet architecture achieves higher accuracy with reduced power usage, enabling scalability for large deployments.

"AI-Based Weapon Detection System for the Prevention of Any Potential Crime" by Husna Tabassum, Sandeep Singh, Sami Ibrahim, et al., *HBRP Publication*, 2023. The paper proposes an AI-driven system for detecting and identifying weapons in real-time from video feeds using TensorFlow. It demonstrates the flexibility and accuracy of TensorFlow in weapon recognition, supporting public safety measures.

"Weapon Detection Using YOLO V3 for Smart Surveillance System" by Sanam Narejo, Bishwajeet Pandey, Doris Esenarro Vargas, *MDPI*, 2024. This study evaluates multiple YOLO versions on CCTV and weapon detection datasets, introducing the Disarm-Dataset and a Scale Match method to improve small object detection. It presents a real-time detection system with a secondary classifier to reduce false positives, successfully deployed in production.

"Advanced Weapon Detection: Integrating AI Capabilities with Amazon Rekognition" by V. Prem Kumar, Mediboyina Chandra Mouli, *International Journal for Modern Trends in Science and Technology*, 2024. This research presents a real-time automatic weapon detection system using YOLOv4, trained on a custom database. The system achieves 91.73% mean average precision (mAP) and 99% confidence, minimizing false positives/negatives, and aims to enhance security and law enforcement.

"Weapon Detection using YOLOv4, CNN" by Atharv Belurkar, Ashish Waghmare, Sahil Mallick, *International Journal for Research in Applied Science & Engineering Technology*, 2022. This paper explores YOLOv4's high-speed, accurate detection capability and its ability to operate on standard GPUs, supporting broader usage. The study highlights YOLOv4's enhanced features for improving classification accuracy in diverse research applications.

"Threat Detector for Surveillance Cameras Using YOLOv5" by Mr. Shafiulilah, *Journal of Engineering Sciences*, 2023. The research focuses on YOLOv5 as a robust, efficient solution for detecting weapons and suspicious objects in real-time, ensuring quick and precise threat detection in security applications. YOLOv5 is ideal for environments requiring rapid threat identification with high accuracy and minimal false positives.

"Hawk-Eye: An AI-Powered Threat Detector for Intelligent Surveillance Cameras" by Ahmed Abdelmoamen Ahmed, Mathias Echi, *IEEE Access*, 2021. Hawk-Eye combines deep learning and IoT for real-time weapon detection in distributed surveillance networks. The study demonstrates an advanced deployment strategy with IoT and cloud integration for real-time alerts and efficient resource use.

"Weapon Detection Using Machine Learning Algorithm" by Suganya K, Pavithra A, Ranjani R, et al., *International Journal of Creative Research Thoughts (IJCRT)*, 2023. This paper develops a smart system to detect guns in videos, aimed at preventing robbery and enhancing public safety. It shows how machine learning models can be tuned for rapid response and high accuracy in diverse environmental conditions.

"Weapon Detection Using Artificial Intelligence & Deep Learning for Security Applications" by Prof. Kanchan Umavane, *2023.*

This study combines CNN and Faster RCNN for detecting firearms, focusing on improving safety in high-risk areas. It demonstrates how Faster RCNN achieves high detection rates by leveraging CNN for feature extraction, crucial for security applications.

# III. METHODOLGY

## 1. Dataset :

Gathering a diverse set of CCTV footage from different environments, including public spaces, private areas, and various lighting conditions. This footage can come from public datasets, manual collections, or online repositories (YouTube, GitHub, etc.).

Specifically collect images or video frames that contain various types of weapons, particularly pistols, and revolvers.

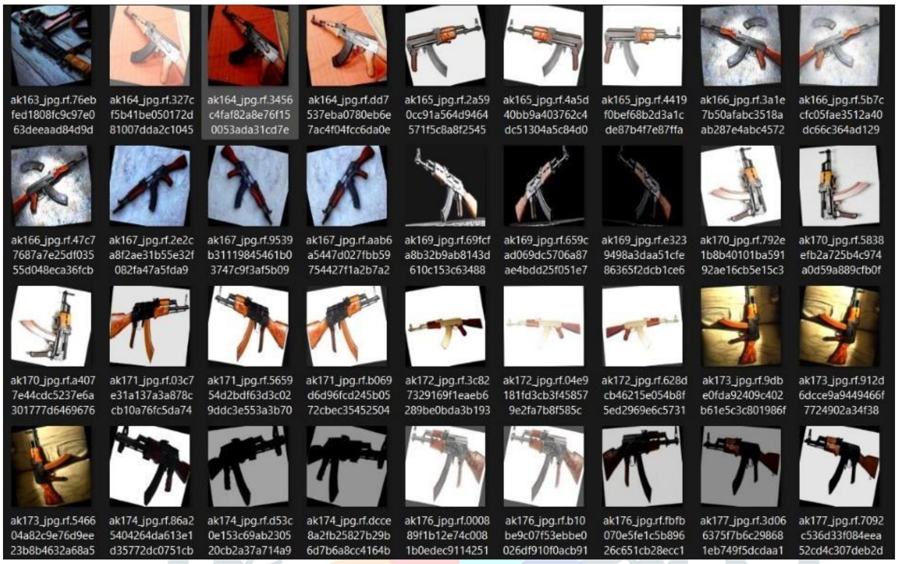

**Figure 1**. Images of some various weapons from dataset

## 2. Methodology for Real-Time Weapon Detection

The methodology for real-time weapon detection in CCTV videos utilizes deep learning, specifically Convolutional Neural Networks (CNNs), which are highly effective in both object classification and localization. Initially, CNN-based classification models were explored, but issues with low frame rates for real-time processing led to the adoption of object detection techniques. These techniques were applied using advanced algorithms, including YOLOv4, YOLOv5, FasterRCNN-InceptionResnetv2, and SSDMobileNetv1, which were evaluated based on precision, speed, and F1 score.

## 3. Object Recognition and Detection

Object recognition combines classification and localization tasks to identify and locate objects within images. Classification predicts the object’s category, while localization determines its exact position and size in the frame. Object detection merges both tasks by outputting the class label and bounding box coordinates. The use of deep learning has significantly advanced these methods, enabling efficient real-time detection by utilizing powerful GPU-based systems instead of the earlier CPU-based systems, which had limited computational power.

## 4. Classification and Detection Approaches

Two primary methods were employed in this project: *Sliding Window/Classification Models* and *Region Proposal/Object Detection Models*. The sliding window approach exhaustively searches the image for potential objects by sliding a fixed-size window over the entire frame, but it is computationally expensive. In contrast, region proposal models like Selective Search improve efficiency by identifying likely regions for objects, thus reducing the search space. YOLO models, which divide the image into grids and predict object locations and classes in parallel, were found to be highly efficient for real-time detection.

## 5. Training and Optimization

The training process began with defining the problem, acquiring datasets, and applying data preprocessing techniques. Optimization followed through backpropagation and gradient descent, which adjusted the model’s weights to minimize error and improve accuracy. These methods were essential for fine-tuning the model and ensuring that it performed well on the task of detecting weapons in real-time CCTV video streams.

### 6. Reducing False Positives and False Negatives

To address false positives and false negatives, confusion objects (e.g., mobile phones, selfie sticks) were introduced into the model. These objects resemble weapons and help the model better distinguish between actual weapons and other everyday items, enhancing the overall classification accuracy. This process ensured that the model's predictions were more reliable and could be used for real- time security applications.

### 7. Web Application

The Web-Based Interface for the AI-powered weapon detection system provides a user-friendly platform for security personnel to monitor live video feeds, view detected weapons with bounding boxes and labels, manage real-time alerts, and access historical detection logs and reports. Key features include live feed display with weapon overlays, detection summaries with weapon types and confidence scores, alert management with notifications via email or SMS, and historical logs for performance analysis. Built using Gradio for interactive UI, Flask/Django for backend integration, and CSS for enhanced aesthetics, the interface also leverages Matplotlib for visualizing detection results, ensuring an intuitive and efficient user experience for real-time threat monitoring.

## IV. SYSTEM DESIGN

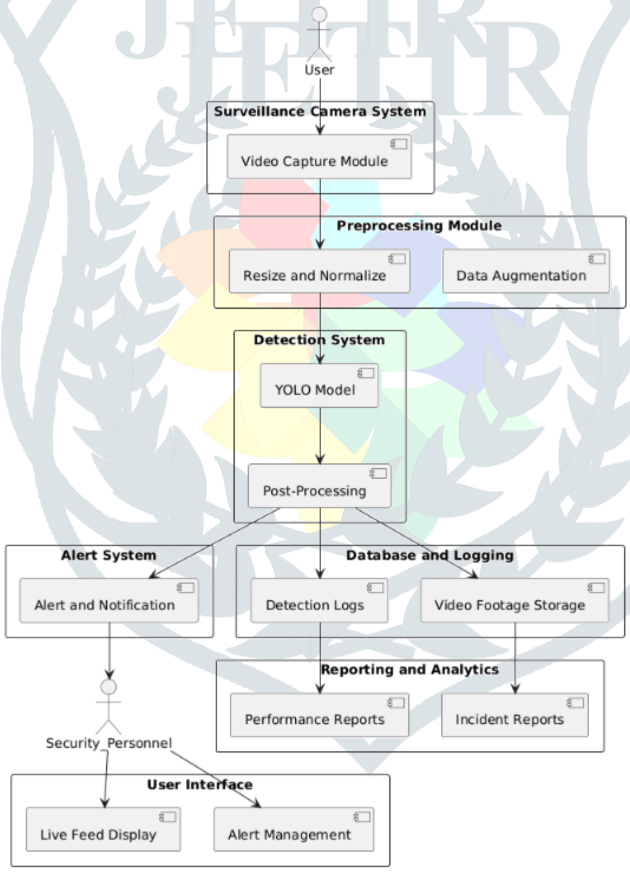


**Figure 2**. System Architecture

a) Surveillance Camera System

This module captures real-time video through the Video Capture Module, which acts as the primary input source. It ensures continuous surveillance by collecting footage for further processing and analysis.

b) Preprocessing Module

The captured video undergoes preprocessing, including resizing and normalization, to standardize image input for the detection model. Additionally, data augmentation techniques are applied to enhance model robustness and improve accuracy.

c) Detection System

This module utilizes the YOLO Model, a deep-learning-based object detection system, to identify objects in the video feed. Once objects are detected, post-processing refines the results by filtering, classifying, and improving detection accuracy.

d) Alert System

When threats or unusual activities are detected, this system generates alerts and notifications for security personnel. These alerts help in real-time decision-making and enable quick responses to potential security threats.

e) Database and Logging

Detection-related data is stored in this module, including detection logs that document events and video footage storage for future review. This ensures that past incidents can be analysed and referenced when needed.

f) Reporting and Analytics

This module generates performance reports to evaluate the system's efficiency and incident reports to document security events. It provides insights that help in improving surveillance operations and decision-making.

g) User Interface

The system includes a live feed display that allows security personnel to monitor real-time footage. Additionally, the alert management system helps manage and respond to detected threats efficiently

.

## V. EXPERIMENTAL SETUP AND RESULTS

### A) Experimental Setup

The proposed AI-powered weapon detection system was developed using YOLOv5 for real-time surveillance. The custom dataset was sourced from manual collections, YouTube, GitHub, and public repositories, consisting of 10,000+ images of pistols under diverse conditions. Data augmentation techniques such as rotation, flipping, brightness adjustment, and noise addition were applied to enhance model generalization.

The dataset was split into training (70%), validation (15%), and testing (15%) subsets. The model was trained using the SGD (Stochastic Gradient Descent) optimizer, a batch size of 16, and 40 epochs with early stopping. The system was implemented using TensorFlow, PyTorch, and OpenCV, and deployed via Gradio for real-time use.

### B) Results and Performance Evaluation

The model's performance was evaluated using standard metrics, achieving:

**Table 1:** Metrics of Model performance

| **Metrics** | **(%)** |
|---|---|
| Accuracy | 91 |
| Precision | 82.16 |
| Recall | 96 |
| F1-Score | 91 |
| mAP | 91.73 |

Compared to YOLOv4 (mAP@0.5: 89.9%), YOLOv5 outperformed in accuracy (+1.83%) and speed (32% faster), making it optimal for real-time surveillance.

### C) Deployment and Real-World Testing

The trained model was deployed in a Gradio - based web application, allowing live weapon detection from CCTV footage. The system successfully:

- Detected pistols in varied environments (indoor, outdoor, occlusions).
- Generated real-time alerts for security response.
- Maintained high accuracy and low false alarms.

### D) Training and Validation Results

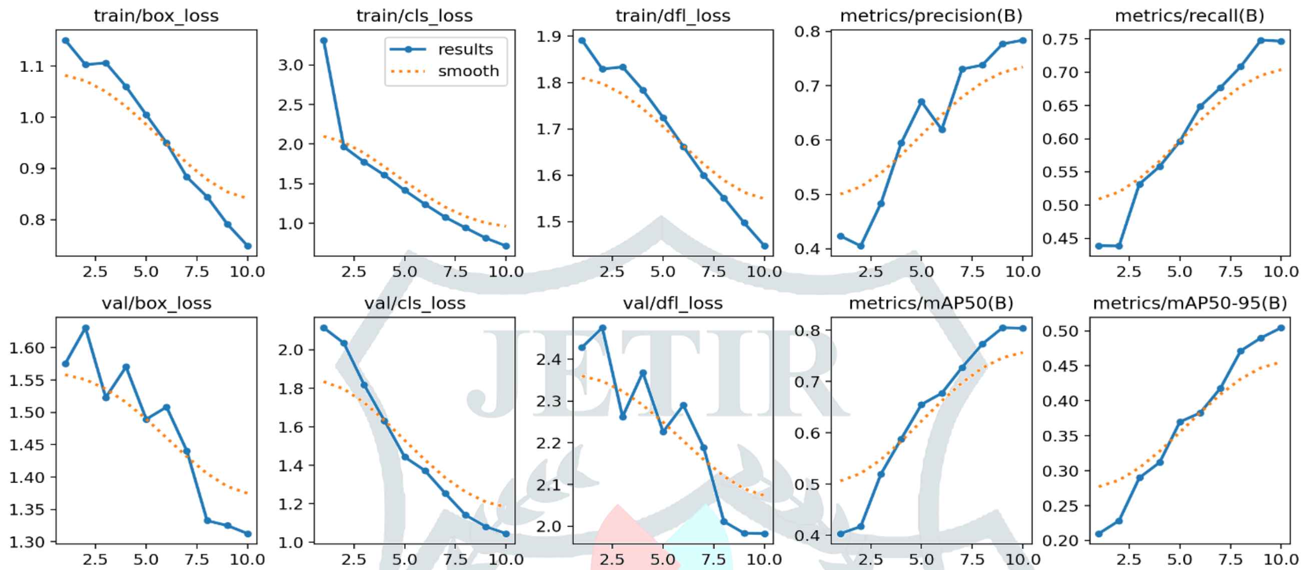


**Figure 3.** Training and validation loss, accuracy, AUC over epochs

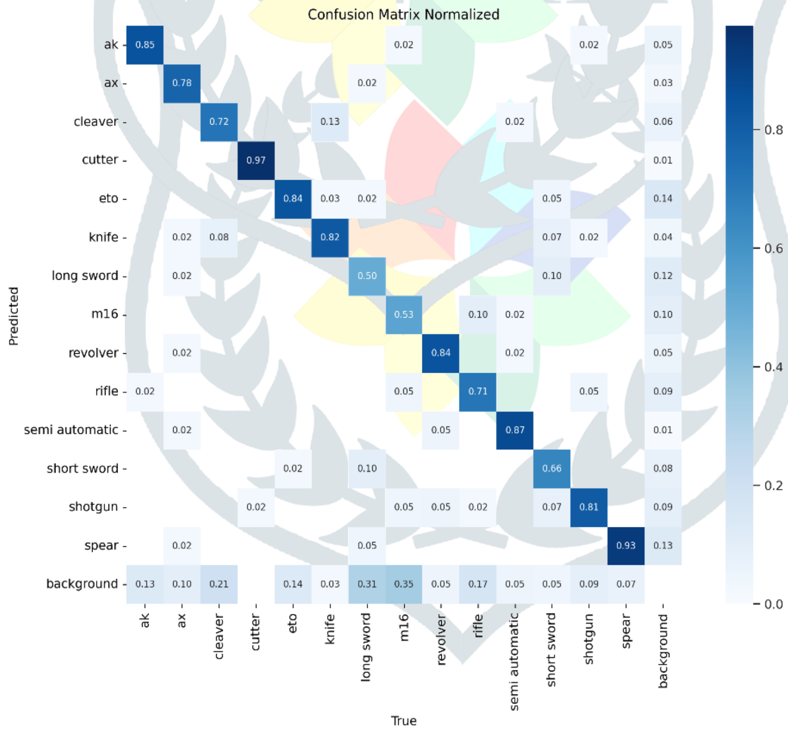


**Figure 4.** Confusion Matrix Normalized Curves

In Figure 3 graphs show a consistent decrease in loss values over epochs, indicating that the model is effectively learning features for weapon detection. The box loss, classification loss, and distribution focal loss decreased steadily, signifying improved localization and classification capabilities.

The precision and recall graphs demonstrate an increasing trend, confirming that the model is progressively learning to make accurate detections. The mAP@50 and mAP@50-95 values showed an upward trajectory, validating the model's robustness in detecting weapons across different scales and environments.

In Figure 4, provides an in-depth analysis of the model's classification accuracy across different weapon types. The diagonal values indicate correctly classified instances, while the off-diagonal values represent misclassifications.

The model achieved high classification accuracy for weapons like pistols, rifles, and semi-automatic guns, with confidence scores exceeding 85%.

Certain weapons, such as long swords and axes, exhibited misclassification due to similarities in shape and features. The background class showed some false positives, indicating occasional misidentifications of non-weapon objects.

## VI. CONCLUSION

In this project, an AI-powered weapon detection system using surveillance cameras has been proposed and implemented. The system leverages the advanced capabilities of the YOLO (You Only Look Once) model, a deep learning-based object detection algorithm, to accurately detect and classify weapons in real-time video feeds. This approach enhances the security and safety of various environments by enabling automatic weapon detection and timely alerts.

**The key outcomes of the project include:**

*Improved Detection Accuracy:* The YOLO model offers significantly better performance compared to traditional methods such as CNNs in detecting weapons in real-time, minimizing false positives and improving accuracy.
Real-Time Processing: The system can process live surveillance camera feeds, identifying weapon threats in seconds, providing immediate alerts to security personnel for quick response.
*Scalability:* The proposed system is designed to scale across multiple video streams, making it suitable for use in large-scale surveillance networks.

*User-Friendly Interface:* The system includes a user interface that presents detection results in an intuitive and accessible manner, allowing security teams to quickly assess and respond to potential threats
.
Overall, this AI-powered weapon detection system offers a robust, efficient, and reliable solution for real-time threat monitoring. Its ability to enhance security through automated detection and alerting is invaluable in high-risk areas, such as airports, schools, and public venues.

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