

# AI-Based Military Threat Detection using YOLOv8

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## ABSTRACT

Artificial Intelligence (AI) and Deep Learning have significantly improved modern surveillance systems by enabling automatic object detection and real-time monitoring. Conventional military surveillance relies on human operators, which may result in delayed threat identification and reduced efficiency. This project proposes a YOLOv8-based Military Object Detection System to detect and classify soldiers, intruders, and weapons from surveillance videos. A custom dataset was created and annotated using Roboflow, then exported in YOLOv8 format to train a custom object detection model using Python, the Ultralytics YOLOv8 framework, and Visual Studio Code. The trained model detects objects in real time by generating

bounding boxes, class labels, and confidence scores. Experimental results show that the proposed system effectively detects soldiers, intruders, and weapons under normal surveillance conditions. Although factors such as limited dataset size and varying lighting conditions affect detection accuracy, the model achieves satisfactory real-time performance. The proposed system demonstrates the potential of deep learning-based object detection for enhancing military surveillance and provides a foundation for future improvements.

**Keywords:** Artificial Intelligence (AI), Deep Learning, YOLOv8, Object Detection, Military Surveillance, Intruder Detection, Weapon Detection, Computer Vision, Roboflow, Real-Time Detection.

# 1.INTRODUCTION

Object detection is one of the most important applications of Artificial Intelligence (AI) and Computer Vision, enabling computers to identify and locate objects in images and videos. Deep learning-based models, particularly the YOLO (You Only Look Once) family, have gained widespread popularity due to their high detection accuracy and real-time processing speed.

In military surveillance, continuous monitoring is essential for detecting unauthorized intruders, soldiers, and weapons. Conventional surveillance systems rely heavily on human operators, making them prone to fatigue, delayed responses, and human errors. These limitations highlight the need for intelligent automated surveillance systems capable of detecting threats quickly and accurately.

The proposed YOLO-Based Military Object Detection system uses the YOLOv8 object detection model to identify soldiers, intruders, and weapons in real time. A custom dataset was manually collected and accurately annotated using Roboflow to improve training quality. The annotated dataset was exported in YOLO format and used to train the model in the Visual Studio Code environment using Python.

The trained model was tested on surveillance videos and successfully detected the predefined object classes by generating bounding boxes, class labels, and confidence scores. Although the detection accuracy can be further improved with a larger dataset and optimized training, the proposed system demonstrates the effectiveness of AI-based object detection for military surveillance by reducing manual monitoring and enabling faster threat identification.

## 2. LITERATURE SURVEY

**Joseph Redmon and Ali Farhadi [1]** (2016) introduced the YOLO (You Only Look Once) object detection algorithm for real-time object detection. The model performs object localization and classification in a single forward pass, providing high detection speed. However, the early version showed reduced accuracy in detecting small objects.

**Joseph Redmon and Ali Farhadi [2]** (2018) proposed YOLOv3, which improved detection accuracy by introducing multi-scale feature prediction. The model demonstrated better performance for detecting objects of different sizes while maintaining real-time processing capability.

**Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao** [3] (2020) developed YOLOv4 to improve the balance between detection speed and accuracy. The model incorporated advanced training techniques and achieved superior performance in various object detection applications.

**Chien-Yao Wang, Alexey Bochkovskiy, and Hong-Yuan Mark Liao** [4] (2023) introduced YOLOv7, which further enhanced object detection through improved feature extraction and optimized network architecture. The model achieved state-of-the-art performance for real-time detection tasks.

**Glenn Jocher, Ayush Chaurasia, and Jing Qiu** [5] (2023) introduced YOLOv8, which employs an anchor-free detection approach with improved feature extraction and faster inference. The model is highly suitable for custom object detection tasks and real-time surveillance applications.

**Divya Kumawat, Deepak Abhayankar, and Sanjay Tanwani** [6] (2023) presented a YOLOv7 and YOLOv8-based weapon detection system for surveillance applications. Their work demonstrated effective real-time weapon detection using deep learning techniques, contributing to improved security and public safety.

A comparative analysis of the existing literature indicates that most object detection systems focus on general object or weapon detection and are trained using publicly available datasets. In contrast, the proposed work develops a custom-trained YOLOv8 model using a manually collected and annotated dataset of soldiers, intruders, and weapons to achieve efficient real-time military threat detection.

### 3. PROBLEM STATEMENT

Military and border surveillance systems require continuous monitoring to detect potential threats and prevent unauthorized access. Traditional surveillance methods rely heavily on security personnel to monitor CCTV footage, making the process time-consuming, labor-intensive, and prone to human error. Continuous observation may lead to fatigue, delayed responses, and missed detections, reducing the effectiveness of security operations.

Although recent deep learning-based object detection models have improved surveillance capabilities, most existing systems are designed for general object detection and are trained using publicly available datasets. These systems are often unable to accurately distinguish between authorized soldiers, unauthorized

intruders, and weapons in military environments. Variations in lighting conditions, object orientation, and complex backgrounds further affect detection performance.

Therefore, there is a need for an intelligent and automated military surveillance system capable of detecting soldiers, intruders, and weapons in real time. The proposed AI-Based Military Threat Detection System uses the YOLOv8 object detection model with a custom manually annotated dataset to improve detection efficiency, reduce human intervention, and support faster threat identification in military and high-security environments.

## **5. EXISTING SYSTEM**

The existing surveillance systems have several limitations that reduce their effectiveness in military security applications.

- Continuous monitoring requires constant human effort and may lead to fatigue and human error.
- Most systems detect only humans or weapons separately and cannot simultaneously identify soldiers, intruders, and weapons.

- Public datasets are not specifically designed for military surveillance, resulting in lower detection accuracy.
- Detection performance decreases under low-light conditions, complex backgrounds, and different viewing angles.
- Most deep learning models require large annotated datasets and high computational resources.
- Manual surveillance increases response time during emergency situations and limits the overall efficiency of military security systems.

## **6. LIMITATIONS OF EXISTING SYSTEM**

- Requires continuous human monitoring, leading to fatigue and human error.
- Cannot simultaneously detect soldiers, intruders, and weapons.
- Public datasets reduce accuracy in military surveillance applications.
- Performance decreases under low-light conditions, complex backgrounds, and different viewing angles.

- Requires large annotated datasets and high computational resources.
- Manual surveillance delays threat detection and reduces overall system efficiency.

**Table 1. Comparison of existing system and proposed system**

| Feature            | Existing System                             | Proposed System                                     |
|--------------------|---------------------------------------------|-----------------------------------------------------|
| Detection Method   | Manual monitoring using CCTV cameras        | AI-based automatic detection using YOLOv8           |
| Objects Detected   | General human detection or weapon detection | Soldiers, intruders, and weapons                    |
| Dataset            | Public or general-purpose datasets          | Custom manually collected dataset                   |
| Processing         | Manual observation                          | Real-time automated detection                       |
| Output             | Surveillance video only                     | Bounding boxes, class labels, and confidence scores |
| Human Intervention | Continuous monitoring required              | Minimal human intervention                          |
| Application        | General security surveillance               | Military surveillance and threat detection          |

**7. PROPOSED SYSTEM**

The proposed system presents an AI-based Military Threat Detection System developed using the YOLOv8 object detection algorithm to automate surveillance in military and high-security environments. Unlike conventional surveillance systems that rely heavily on human monitoring, the proposed approach automatically detects and classifies soldiers, intruders, and weapons from real-time video input.

Initially, a custom dataset was created by collecting hundreds of images representing three different classes: soldiers, intruders, and weapons. To ensure high-quality annotations and reduce labeling errors, every image was manually labeled using the Roboflow annotation platform. The annotated dataset was then exported in YOLO format and used to train the custom YOLOv8 model.

The model training process was carried out using Visual Studio Code, where the dataset configuration and training parameters were defined. The model was trained for approximately 40 epochs, allowing it to learn distinctive visual features associated with each object class. After completion of training, the trained model weights were used for inference on surveillance videos.

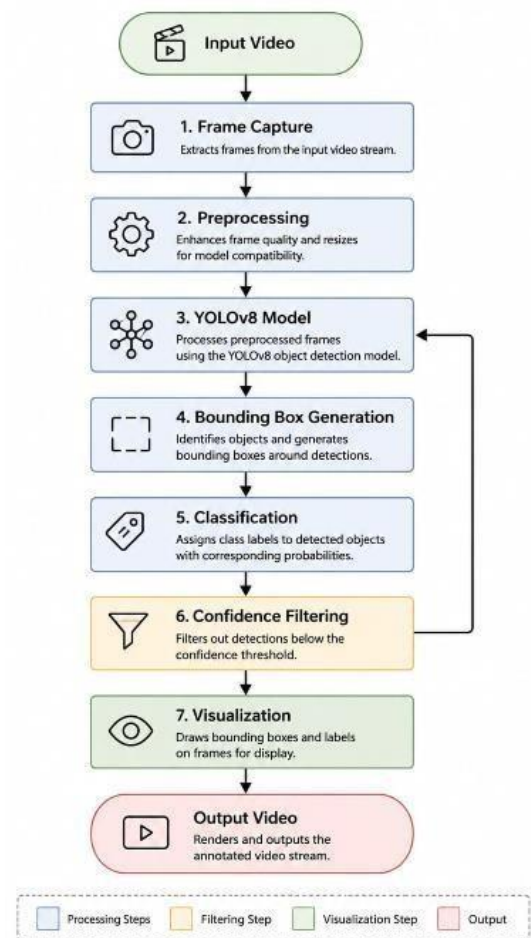
During testing, the system processes each video frame and applies the trained YOLOv8 model to identify objects of interest. Detected objects are displayed with bounding boxes, corresponding class labels, and confidence scores, enabling security personnel to quickly recognize potential threats. The proposed system successfully detects soldiers, intruders, and weapons from video input while demonstrating the feasibility of AI-based automated military surveillance.

Although the current model produces satisfactory detection results, its performance can be further improved by increasing the dataset size, incorporating more diverse training images, optimizing hyperparameters, and extending the number of training epochs. Nevertheless, the proposed system demonstrates the effectiveness of custom-trained YOLOv8 models in supporting intelligent military surveillance and reducing dependence on continuous manual monitoring.

## 8. SYSTEM ARCHITECTURE

The architecture of the proposed AI-Based Military Threat Detection System consists of several interconnected modules that work together to detect soldiers, intruders, and weapons from surveillance videos in real time. The overall workflow begins

with video acquisition and proceeds through frame preprocessing, object detection, classification, confidence filtering, visualization, and output generation.



Initially, the system receives video input through a surveillance camera or a pre-recorded video file. The captured video is divided into individual frames using the OpenCV library. Processing the video frame by frame enables the system to perform real-time object detection while maintaining efficient computational performance.

Each extracted frame undergoes preprocessing before being forwarded to the detection model. During preprocessing, the frames are resized to the required input dimensions of the YOLOv8 model and normalized to improve detection efficiency and ensure compatibility with the trained network. This preprocessing stage helps the model process images consistently regardless of their original resolution.

The preprocessed frames are then passed to the trained YOLOv8 object detection model. The model analyzes each frame by extracting important visual features and predicts the presence of objects belonging to the predefined classes. In this work, the trained model identifies three object categories: soldiers, intruders, and weapons. For every detected object, the model generates the corresponding bounding box coordinates, class label, and confidence score.

After detection, confidence score filtering is performed to eliminate low-confidence predictions that may lead to false detections. Only detections with confidence values above the predefined threshold are retained for further processing. This filtering process improves the reliability of the final output by reducing unnecessary or incorrect detections.

The filtered detection results are then forwarded to the visualization module. In this stage, bounding boxes are drawn around the detected objects, and the corresponding class labels along with confidence scores are displayed on each video frame. This visual representation enables security personnel to quickly identify authorized soldiers, unauthorized intruders, and weapons present within the surveillance area.

Finally, all processed frames are combined sequentially to generate the output video. The resulting video displays real-time detection results with clearly marked objects, providing an intelligent surveillance solution capable of assisting military personnel in monitoring restricted areas and identifying potential threats efficiently.

## **9. METHODOLOGY**

The proposed AI-Based Military Threat Detection System was developed using the YOLOv8 object detection model to automatically identify soldiers, intruders, and weapons from surveillance videos. The complete methodology consists of six major phases: dataset collection, data annotation, dataset preparation, model training, model testing, and result

generation. The overall workflow is designed to develop a reliable object detection model capable of performing real-time military surveillance.

## 9.1 Dataset Collection

The first phase involved collecting a custom dataset for training the object detection model. Hundreds of images belonging to three different classes—**Soldiers**, **Intruders**, and **Weapons**—were collected from various reliable sources. The dataset included images captured under different backgrounds, lighting conditions, object orientations, and viewing angles to improve the model's ability to generalize to different surveillance environments. Since publicly available datasets do not adequately represent military scenarios, a custom dataset was created specifically for this application.

## 9.2 Data Annotation

After collecting the images, the dataset was manually annotated using the **Roboflow** platform. Each object in every image was carefully labeled according to its corresponding class, namely Soldier, Intruder, or Weapon. Manual annotation was preferred over automated labeling to reduce labeling errors and improve dataset quality. Accurate annotation enables the YOLOv8 model to learn object locations

and class information more effectively, thereby improving detection performance.

## 9.3 Dataset Preparation

Once the annotation process was completed, the dataset was exported from Roboflow in the YOLOv8-compatible format. The exported dataset contained training, validation, and testing images along with their corresponding annotation files. This structured dataset was then organized and prepared for model training in the Visual Studio Code environment.

## 9.4 Model Training

The YOLOv8 object detection model was trained using the prepared custom dataset. The training process was carried out in Visual Studio Code by configuring the dataset path, model parameters, and training settings. The model was trained for approximately **40 epochs**, during which it learned the distinguishing visual characteristics of soldiers, intruders, and weapons. During each epoch, the model continuously updated its weights to minimize detection errors and improve classification performance.

## 9.5 Model Testing

After completing the training process, the trained YOLOv8 model was evaluated using input surveillance videos. The video was processed frame by frame, and each

frame was analyzed to identify the predefined object classes. The trained model generated bounding boxes around detected objects while displaying the corresponding class labels and confidence scores. This testing phase verified the model's capability to perform real-time object detection on unseen video data.

## **9.6 Output Generation**

The final output of the proposed system consists of processed surveillance video frames showing the detected soldiers, intruders, and weapons. Each detected object is highlighted using a bounding box along with its corresponding class label and confidence score, making it easier to identify and monitor potential threats. The processed output demonstrates the capability of the trained YOLOv8 model to perform real-time object detection with satisfactory accuracy and efficiency in military surveillance applications.

The generated output provides a clear visualization of all detected objects, enabling security personnel to identify threats quickly and effectively. Although the current model achieved successful detection, the overall accuracy can be further improved by increasing the dataset size, incorporating more diverse training samples collected under different environmental conditions, and optimizing

the training parameters.

These improvements can further enhance the robustness and reliability of the proposed military threat detection system.

# **10. RESULTS AND DISCUSSION**

## **10.1 Performance Analysis**

The proposed AI-Based Military Threat Detection System was tested using surveillance videos containing soldiers, intruders, and weapons. The trained YOLOv8 model successfully detected and classified the objects by generating bounding boxes, class labels, and confidence scores in real time.

The custom dataset, manually annotated using Roboflow, improved the training quality and detection performance. However, accuracy was affected by the limited dataset, complex backgrounds, and different viewing angles. Increasing the dataset size and optimizing the training process can further improve the model's performance.

Overall, the proposed system demonstrates the effectiveness of YOLOv8 for automated military surveillance and real-time threat detection.

## 10.2 Output Visualization

The proposed system successfully detected and classified soldiers, intruders, and weapons using the trained YOLOv8 model. During testing, the input video was processed in real time, and detected objects were displayed with bounding boxes, class labels, and confidence scores.

The results demonstrate that the model can simultaneously detect multiple object classes, making it suitable for intelligent military surveillance and automated threat detection. The output screenshots obtained during testing are presented below to illustrate the detection performance of the proposed system.

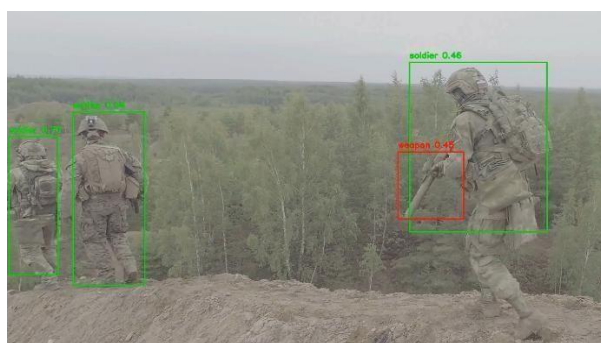
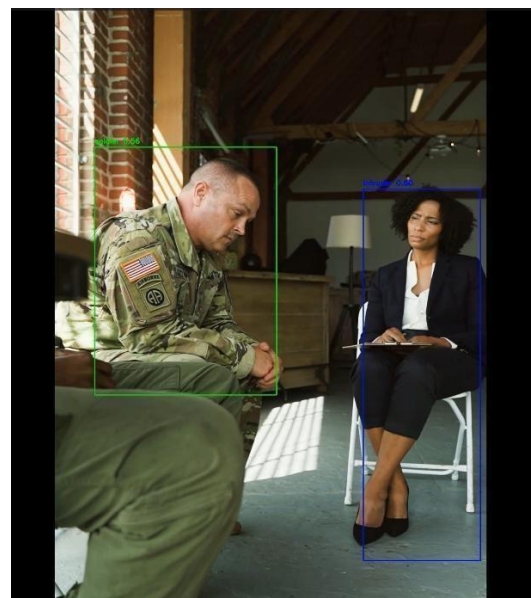
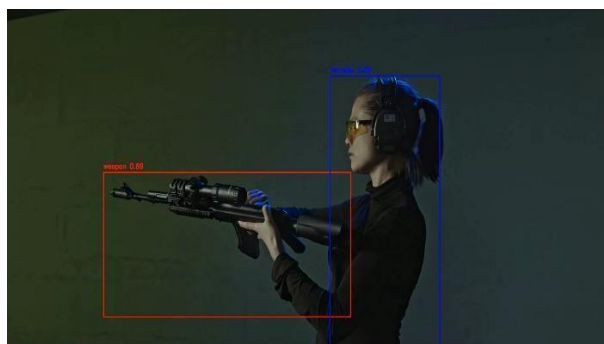
**Fig. 1. Detection of Soldiers**



**Fig. 2. Detection of Intruders**



**Fig. 3. Detection of Weapons**



## 11. CONCLUSION

This paper presented an AI-Based Military Threat Detection System using the YOLOv8 object detection model for intelligent military surveillance. A custom dataset of soldiers, intruders, and weapons was manually collected and annotated using Roboflow, and the model was trained and tested using surveillance videos. The system successfully detected the predefined object classes by generating bounding boxes, class labels, and confidence scores in real time. Although the model achieved satisfactory detection performance, its accuracy can be further improved by increasing the dataset size and optimizing the training process. Overall, the proposed system provides an efficient and reliable solution for automated military threat detection.

## 12. FUTURE SCOPE

The proposed AI-Based Military Threat Detection System can be further enhanced to improve its performance and real-world applicability.

1. **Expansion of Dataset:** Increase the dataset by including more diverse images captured under different lighting conditions,

backgrounds, and viewing angles to improve detection accuracy.

2. **Detection of Additional Military Objects:** Extend the system to detect military vehicles, drones, explosives, and other defense equipment for enhanced surveillance.
3. **Real-Time Deployment:** Deploy the trained YOLOv8 model on edge devices such as NVIDIA Jetson or Raspberry Pi for real-time military surveillance.
4. **Integration with Intelligent Alert Systems:** Integrate the system with mobile applications or command-and-control systems to provide instant alerts whenever threats are detected.

These enhancements will improve the accuracy, efficiency, and scalability of the proposed military surveillance system.

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