Real-Time Military Threat Detection Using YOLOv8 with Web-Based Surveillance Dashboard

Eshwar Sai Reddy Mudumala, VishnuVardhan Chittem, Sai Karthik Mukunda, Anusaya Swain
Department of Electronics and communication Engineering
Amrita School of Engineering Bengaluru
Amrita Vishwa Vidyapeetham India
eshwarsaireddymudumala@gmail.com, chittamvishnuvardhan@gmail.com, mukundasaikarthik@gmail.com,
s_anusaya@blr.amrita.edu

***Abstract*—On time threat detection is now a significant need of the contemporary military surveillance systems wherein swift and precise identification of the potential danger could greatly increase the safety of operation. The paper proposes a deep learning-based method of military threats detection based on the YOLOv8 object detection model combined with a web-based monitoring dashboard. The suggested system will recognize several classes which are weapons, personnel, military vehicles and landmines just to mention but a few through the live video streams obtained using a mobile camera on a common network. The backend takes raw video frames in real time, objects are detected and the results with annotations are sent to a user-friendly dashboard to be visualized and generate alerts. The system focuses on low latency and high detection rates as well as is easy to deploy in resource-constrained settings. Through experimental results, it has been observed that the model has efficient real time performance that is applicable in surveillance. Mobile streaming technology and web technologies also enable accessibility and scalability to field deployment.**

***Index Terms*—YOLOv8, Military Surveillance, Object Detection, Real-Time Systems, Threat Detection, Computer Vision.**

I. INTRODUCTION

There has been an increase in the number of requests for smart surveillance systems in recent years. However, most traditional methods are reliant on people's abilities to monitor images. In most cases, this can lead to delays in action and the occurrence of human-related mistakes due to tiredness. With the help of advanced artificial intelligence and deep learning techniques, the development of an automated system for detecting objects has become possible [1].

The process of detecting specific entities is very important when trying to get information about particular items in a picture. It is worth noting that there exist various machine learning architectures; however, YOLO (You Only Look Once) algorithms seem to be particularly useful when one needs to perform this task quickly and accurately. As for the latest YOLO version – YOLOv8, it has certain advantages that can make it suitable for military tasks [2].

First of all, military settings involve many variables and can be unpredictable. This is why the system used for object detection must be robust and able to work effectively despite any possible complications. Moreover, it should be noted that the ability to work in real time is crucial in this case. Besides that, the convenience of user interface is also important since military experts need information immediately [3].

This research proposes the development of a system of real-time military threat detection. The algorithm will be based on a trained deep learning model that uses YOLOv8 as a basis. Moreover, the system's output will be presented in a convenient and understandable way by creating a custom dashboard on the web.

The source of input data will be a mobile camera, and it will be connected to the computer via the local area network. This method will not require additional hardware components. Thus, it will enable flexibility of implementation. Apart from this, another advantage of this system consists in its ability to detect multiple object classes [4] [5].

Finally, it should be stated that backend processing and frontend visualization create a convenient pipeline for data collection, interpretation, and representation. This system is built using some of the most efficient frameworks for processing information and can function on almost any computer.

To sum up, the current paper aims to develop an effective and reliable threat detection system for military purposes based on advanced deep learning models and other modern technologies.

II. LITERATURE REVIEW

Modern progress in computer vision techniques has considerably increased the performance of object detection models in surveillance technologies. Particularly, a wide variety of the YOLO (You Only Look Once) models based on a one-stage approach to detection have become popular owing to their ability to detect targets in real time. While previous models like YOLOv3 and YOLOv4 offered a balanced ratio of detection accuracy and computational efficiency, modern versions, such as YOLOv7 and YOLOv8, have proven to be superior in terms of performance and features' extraction capacity [6], [7].

Among the applications of YOLO models in surveillance is security and defense-related technologies. In [8] pointed out the applicability of YOLOv8 to detect military equipment under challenging visual conditions and its ability to increase detection accuracy compared to other models. Besides, the application of YOLO-based models for aerial surveillance with the help of unmanned aircraft vehicles (UAVs) was analyzed by Solovei [9], which proved its suitability for performing accurate object detection in real time.

Moreover, an increasing number of studies focus on weapon detection through deep learning algorithms. For instance, Deshpande et al. [10] developed a YOLOv8-powered weapon detection system capable of working efficiently under various conditions. Another example is the comparative analysis of different YOLOv8-based models, which showed increased accuracy in weapon detection and fast detection speed [11].

Also worth mentioning is hazardous objects detection with the use of AI-powered models. The work of Levchenko et al. [12] explores the problem of AI-assisted detection of landmines and explosive devices in different settings. Finally, some researchers explore hybrid deep learning algorithms incorporating transformers and YOLOv8 models [13].

Although YOLOv8 shows impressive results in target detection under challenging conditions, several issues can arise while deploying a real-time surveillance system. First of all, the majority of scientific papers do not focus on how models can be implemented into practice; specifically, most studies do not consider a convenient way of video streaming and visualization of detected objects. Thus, the current project expands the scope of research by implementing YOLOv8-based models into a web-based surveillance application.

III. METHODOLOGY

A. System Overview

The suggested system is formed as a pipeline at the end-to-end, which includes the video capture, object detection, and visualization. It incorporates a mobile camera, a backend based on YOLOv8, and a frontend dashboard that is based on a web interface.

B. System Architecture

This fig 1 represents the flow of the suggested intelligent detection system, starting from input acquisition up to making decisions and logging.

Initially, the system self-initiates, loading all the necessary modules to be used. It is followed by a mode selection state where the users can choose an image input or provide live video streaming on a mobile phone.

A decision block examines whether the mode chosen is any of the following:

Provided that an image mode had been chosen, the system would receive an input of the local system in the shape of a fixed image. In the event of video mode being chosen, the system will connect to a mobile phone that has a camera via its IP address and access live video casting. No matter what input was selected, it undergoes a pre-processing step that makes sure that the input meets the requirements of the detection model. That is, the input is standardised.

Next, a pre-trained YOLOv8 model (best.pt) is loaded into the system. It uses this model to identify items within the input. It then classifies them into landmines, firearms, humans or military vehicles.

Then, the system determines the presence of a threat. In the case of yes, it performs the detection results and reports them to the backend server, showing on the front end dashboard. Also, the alerting mechanism is activated at once. Otherwise, the system will record a safe status on the frontend dashboard..

C. Data Acquisition

The smartphone camera is used to record live videos via a local network. The video stream is viewed by means of IP-based URL, which allows obtaining real-time frames without any extra hardware.

D. Dataset Preparation

To train the model on four classes (weapons, persons, military vehicles, and landmines), a custom dataset was created. The publicly available open-source datasets were gathered and annotated with the help of the LabelImg annotation tool. Data augmentation techniques of rotation, scaling, and horizontal flipping were used to enhance model robustness and generalization. [14].

E. Model Training (YOLOv8)

The pre-processed data set is used to train the YOLOv8 algorithm where input images go through image processing using convolutional neural network (CNN) layers before performing bounding box regression and object classification. In the optimization process of the model, Complete Intersection Over Union (CIoU) loss function is used for bounding box regression, while binary cross entropy loss is utilized for classification.

TABLE I
PERFORMANCE METRICS OF THE PROPOSED MODEL

Precision	**Recall**	**mAP**
0.89	0.94	0.96

F. Real-Time Detection

The trained model is implemented in a Python (Flask/FastAPI) based backend. Video frames are constantly captured, processed and fed into the YOLOv8 model to make an inference. Bounding boxes and labels are used to indicate objects identified [15].

G. Web Dashboard Integration

The Web Dashboard makes use of the live stream to present real-time video feeds, as well as detect objects that have been tagged and highlight them. It also raises an alert for any identified threats. The updates take place constantly via API requests.

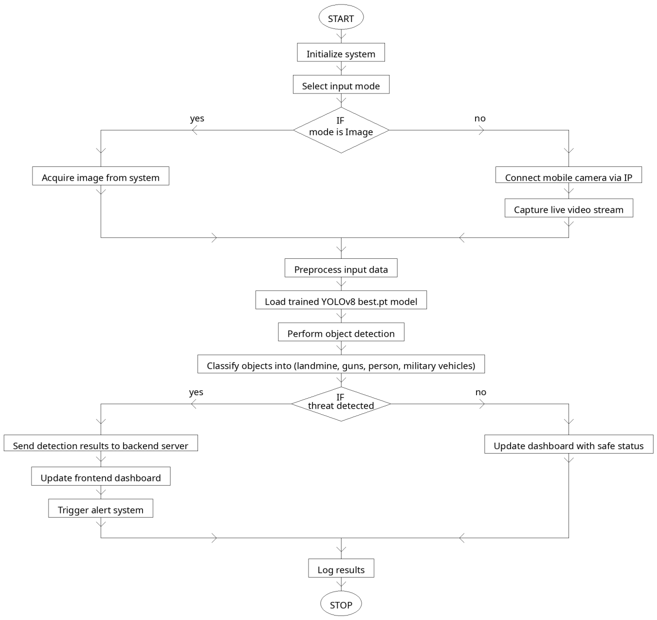


Fig. 1. System Architecture of Proposed Military Threat Detection System

H. System Workflow

The system captures the live streaming video in real time and processes the video frames from it. The processed video frames are analyzed via the YOLOv8 model. Detected objects are then annotated, and the outputs are displayed on the dashboard.

IV. RESULTS AND ANALYSIS

A. Result Metrics

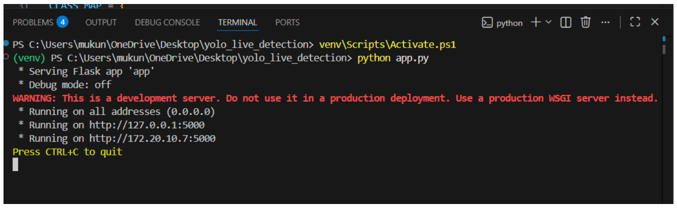
The evaluation of the proposed military object detection system based on the YOLOv8 algorithm is conducted using the following metrics.

TABLE II
PERFORMANCE METRICS OF DETECTION SYSTEM

Parameter	**Value**
Accuracy (Person)	0.85
Accuracy (Tank)	0.88
Accuracy (Gun)	0.92
Accuracy (Landmine)	0.93
Preprocessing Time	2.3 ms
Inference Time	50.9 ms
Post-processing Time	1.3 ms
Detection Speed	≈ 18–20 FPS
Multi-class Detection	Human, Gun, Tank, Landmine

B. Result Analysis

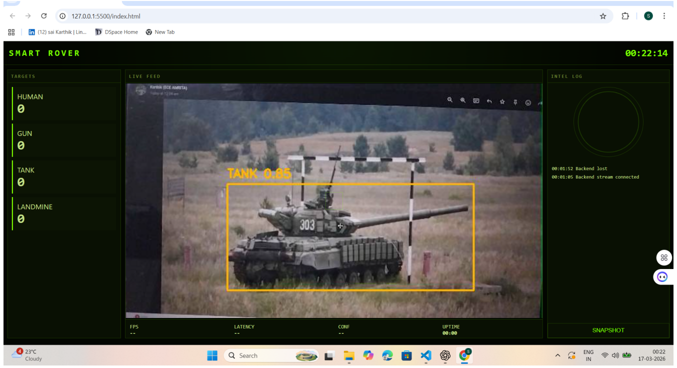
1) Backend Server Initialization: As demonstrated in Fig. 2, the Flask-based backend server is successfully initialized and operates on both localhost and network IP address, enabling real-time interaction.



```
PS C:\Users\mukun\OneDrive\Desktop\yolo_live_detection> venv\Scripts\Activate.ps1
(venv) PS C:\Users\mukun\OneDrive\Desktop\yolo_live_detection> python app.py
 * Serving Flask app 'app'
 * Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on all addresses (0.0.0.0)
 * Running on http://127.0.0.1:5000
 * Running on http://172.20.10.7:5000
Press CTRL+C to quit
```

Fig. 2. Backend server initialization using Flask framework.

2) Real-time Dashboard Interface: Fig. 3 illustrates the SMART ROVER dashboard showing live video feed, detected target categories, and backend server logs.



```
00:01:52 Backend lost
00:01:05 Backend stream connected
```

Fig. 3. Real-time dashboard interface with live detection feed.

3) Human Detection: As depicted in Fig. 4, the proposed system correctly identifies a person with a confidence score of 0.85.

```
...  Enter image path from Drive: /content/drive/MyDrive/testingimages/testing/person1_test.jpg

     image 1/1 /content/drive/MyDrive/testingimages/testing/person1_test.jpg: 640x448 1 person, 50.9ms
     Speed: 2.3ms preprocess, 50.9ms inference, 1.3ms postprocess per image at shape (1, 3, 640, 448)
     Results saved to /content/runs/detect/predict

     Final Detection:
     Detected Class: person
     Accuracy (Confidence): 0.85
```

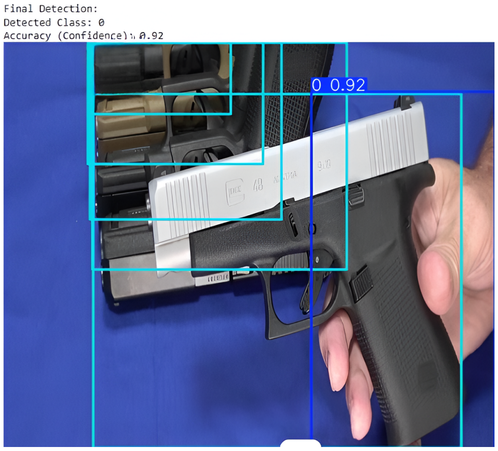
Fig. 4. Detection of a person with confidence score 0.85.

4) *Tank Detection:* Fig. 5 presents successful tank detection with a confidence score of 0.88.

```
Final Detection:
Detected Class: tank
Accuracy (Confidence): 0.88
```

Fig. 5. Detection of a tank with confidence score 0.88.

5) *Gun Detection:* As presented in Fig. 6, the developed application effectively recognizes guns with a confidence score of 0.92.



```
Final Detection:
Detected Class: 0
Accuracy (Confidence): 0.92
```

Fig. 6. Detection of gun with confidence score 0.92.

6) *Landmine Detection:* Fig. 7 indicates that the solution reliably detects landmines with a confidence score of 0.93.

```
Final Detection:
Detected Class: landmines
Accuracy (Confidence): 0.93
```

Fig. 7. Detection of landmine with confidence score 0.93.

V. IMAGE-BASED DETECTION OUTPUT

A. *Discussion*

The system was built on YOLOv8, combining a Python backend with a web-based frontend for seamless operation. The custom dataset was split into training and validation subsets, with normalization and augmentation applied during preprocessing to improve robustness. Training ran for 70 epochs using SGD, with a learning rate of 0.01 and batch size of 16. Bounding box regression, classification, and distribution focal loss jointly guided the optimization process. For deployment, a mobile IP camera served as the live input source, enabling continuous detection in real-time conditions. Across all target classes, confidence scores consistently crossed the 0.85 threshold, reflecting strong model reliability. The end-to-end pipeline maintained a throughput of 18–20 frames per second with negligible latency, demonstrating that the system is well-suited for practical field surveillance

B. *Comparison with Existing Systems*

TABLE III
COMPARISON OF PROPOSED SYSTEM WITH EXISTING METHODS

Parameter	**Existing Systems**	**Proposed System**
Real-Time Detection	Offline / recorded video	Live mobile IP camera
System Integration	Model only	End-to-end system
Detection Model	YOLOv3 / YOLOv4	YOLOv8
Class Detection	Single / limited	Multi-class (4 types)
User Interface	Minimal / none	Web dashboard
Deployment	Research-focused	Real-time deployment

The experimental evaluation reveals that the proposed system achieves measurable improvements in detection performance while simultaneously offering a comprehensive real-time surveillance framework. Unlike existing methodologies, which predominantly address isolated aspects of the detection pipeline, the proposed approach consolidates multiple functional components into a unified architecture, thereby mitigating the operational constraints inherent in prior works

C. Comparative Performance Evaluation of YOLOv8 and MobileNet-SSD for Military Threat Detection

The experimental evaluation reveals evident superiority in performance of the proposed YOLOv8 model over MobileNet-SSD across all major detection measures, as presented in Table IV. MobileNet-SSD recorded a precision of 0.7167, recall of 0.6542, and approximate mAP of 0.8214, whereas the YOLOv8 model demonstrated a significantly better precision of 0.89, recall of 0.94, and mAP of 0.90.

TABLE IV
PERFORMANCE COMPARISON OF YOLOV8 AND MOBILENET-SSD

Metric	**MobileNet-SSD**	**YOLOv8 (Proposed)**
Precision	0.7167	0.89
Recall	0.6542	0.94
mAP	0.8214	0.90

These results are attributable to the anchor-free detection head, enhanced feature pyramid network, and deeper convolutional backbone architecture employed by YOLOv8, as opposed to the comparatively shallow depthwise separable convolution network utilised by MobileNet-SSD. Furthermore, YOLOv8 sustains real-time processing throughput at approximately 18–20 frames per second, whereas MobileNet-SSD demonstrates inferior recall particularly across small and partially occluded targets such as landmines and personnel.

VI. CONCLUSION AND FUTURE SCOPE

This paper presented a real-time military threat detection system built upon the YOLOv8 architecture, integrated with a web-based surveillance dashboard for live operational monitoring. The proposed prototype was evaluated across four target categories, namely personnel, firearms, landmines, and military vehicles, achieving an overall precision of 0.89, recall of 0.94, and mean Average Precision of 0.90, with a real-time throughput of approximately 18–20 frames per second. These results validate the feasibility of the proposed framework as a reliable and computationally efficient prototype-stage surveillance system.While the proposed system yields encouraging detection outcomes at the prototype stage, continued refinement remains essential to strengthen operational performance and broaden applicability toward real-world deployment scenarios. Subsequent research will prioritize dataset expansion through acquisition of diverse and class-balanced annotated samples, addressing per-class instance insufficiency and strengthening model generalization across underrepresented target categories. The incorporation of attention-based mechanisms and transformer-driven architectures, notably Detection Transformer, presents a viable direction for improving localization accuracy of small-scale and partially occluded targets, particularly landmines within complex background conditions. From a scalability standpoint, extending the architecture to support synchronized multi-camera input streams alongside cloud-integrated storage infrastructure would enable distributed and remotely accessible surveillance operations, overcoming the single-feed constraint of the present prototype. Additionally, embedding automated alert mechanisms with threshold-driven notification pipelines would augment real-time situational awareness and reduce operator response latency under time-critical conditions Furthermore, the integration of autonomous threat prioritization and alert mechanisms will be pursued, enabling the system to support time-critical operator decision-making without manual intervention, ultimately advancing the prototype toward a fully deployable intelligent surveillance solution.

REFERENCES

[1] T. S. Reddy and D. Radha, "Object detection and lane detection for autonomous driving," in *2025 2nd Asia Pacific Conference on Innovation in Technology (APCIT)*, 2025, pp. 1–6.

[2] Y. Khare, T. V. Chandran, A. Ramesh, A. KG, and L. S. Nair, "Automatic target detection in cluttered infrared imagery using background modeling approach," in *2022 6th International Conference on Trends in Electronics and Informatics (ICOEI)*, 2022, pp. 1615–1619.

[3] P. Krishnan, S. Kattamuri, G. R. Prabhu, and M. Rashmi, "Assistive eye: A comparative analysis of yolo object detection models on edge devices," in *Proceedings of the 2024 Sixteenth International Conference on Contemporary Computing*, 2024, pp. 104–108.

[4] V. M. Vanmathi, P. Aakash, G. Balajuram, R. Abhishek, S. K. Thangavel, K. Somasundaram, and S. K. Shanmugam, "An intelligent road lane monitoring system using computer vision techniques," in *2024 4th International Conference on Sustainable Expert Systems (ICSES)*, 2024, pp. 1836–1842.

[5] V. D. Kumar, M. Preetham, V. S. Preetham, A. Swain, and S. Kochuvila, "Deep learning based framework for explainable melanoma detection in clinical applications," in *2025 4th International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, 2025, pp. 1605–1610.

[6] P. Veerendernath, V. K. Minchula *et al.*, "Development of an intelligent autonomous rover with distributed sensors for speed control and obstacle avoidance," pp. 1–5, 2025.

[7] N. Bhavana, M. M. Kodabagi, B. M. Kumar, P. Ajay, N. Muthukumaran, and A. Ahilan, "Pot-yolo: Real-time road potholes detection using edge segmentation-based yolo v8 network," *IEEE Sensors Journal*, vol. 24, no. 15, pp. 24 802–24 809, 2024.

[8] M. R. Kumar, N. Rengalakshmi, R. S. Shree, R. Akiladevi, and P. Kumar, "Deep learning for crop disease detection using yolov8," pp. 1–6, 2024.

[9] R. Vaghela, D. Vaishnani, P. N. Srinivasu, Y. Popat, J. Sarda, M. Woźniak, and M. F. Ijaz, "Land cover classification for identifying the agriculture fields using versions of yolo v8," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2025.

[10] B. Karthika, M. Dharssinee, V. Reshma, R. Venkatesan, and R. Sujarani, "Object detection using yolo-v8," pp. 1–4, 2024.

[11] M. Darji, K. Patel, B. Patel, K. Thakkar, M. Minat, and M. K. Patel, "Yolov8-based deep learning model for improved drone intrusion detection," pp. 1178–1184, 2024.

[12] U. Nishitha, V. Lokesh, T. Kaushik, and R. P. Singh, "Vehicle detection in unmanned aerial imagery through advance you only look once architectures," pp. 1–6, 2024.

[13] R. Srinivasan, D. Rajeswari, A. Arivarasi, and A. Govindasamy, "Real-time vehicle classification and license plate recognition via deformable convolution-based yolo v8 network," *IEEE Sensors Journal*, vol. 24, no. 23, pp. 39 771–39 778, 2024.

[14] P. Chaitra, B. Poojitha, G. V. Nikitha, and N. Neelima, "Real-time gesture and sentence level sign language translator," in *2024 Fourth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*, 2024, pp. 1–5.

[15] S. K. Mukunda, V. Chittem, S. Giliaka, N. N, and K. S. Pande, "Posesculpt: Real-time ai-driven posture aligner and corrector," in *2025 10th International Conference on Communication and Electronics Systems (ICCES)*, 2025, pp. 1860–1865.