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GuardVision: An Enhanced Weapon Detection using Computer Vision with Alert Mechanism

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Abstract :

In the modern era, where public safety is paramount, there is an increasing need for intelligent surveillance systems capable of real-time threat detection. GuardVision addresses this need by utilizing cutting-edge computer vision techniques to detect weapons in images, videos, and live webcam feeds. Our system leverages the YOLOv8 object detection model, known for its speed and accuracy, to identify potential threats such as guns or knives. Once the input is processed and a weapon is detected, the system immediately initiates a multi- channel alert mechanism, notifying relevant personnel via email, SMS, and an audible alarm on the system's dashboard. This comprehensive alert system ensures that authorities can respond swiftly to any potential danger, making GuardVision an essential tool for enhancing security in sensitive environments, public spaces, and high-risk areas. Through extensive testing, the system has proven its efficiency and reliability across a variety of conditions.

IndexTerms **- Weapon Detection, YOLOv8, Computer Vision, Alert Mechanism.**

Introduction

GuardVision is a pioneering weapon detection system that leverages advanced computer vision technology to enhance security measures. This innovative project offers a versatile platform for identifying potential threats through multiple input channels: static image analysis, video scrutiny, and realtime webcam monitoring. At its core, GuardVision employs sophisticated preprocessing algorithms to optimize each input, ensuring high accuracy across all detection modes. The system's standout feature is its comprehensive alert mechanism, which deploys a three-pronged approach upon weapon detection: instantaneous email alerts,

rapid SMS notifications, and an audible dashboard alarm. By combining cutting-edge visual recognition with an intelligent notification system, GuardVision aims to create safer environments and equip security teams with the tools necessary to swiftly respond to and mitigate potential risks.

Motivation

The need for this paper arises from increasing concerns about public safety and the limitations of traditional security methods like manual inspection and CCTV surveillance. These conventional methods often fail due to human error and the inability to provide real- time, accurate threat detection. By leveraging computer vision and automation, this paper aims to significantly improve security measures by reducing reliance on manual monitoring and increasing the speed and accuracy of weapon detection.

Literature Survey

Sr. No.	Paper Title and Author	Details of Publication	Methodology	Description
1.	Weapon Detection in Surveillance Videos Using YOLOV8 and PELSF-DCNN, Dr Raman Dugyala1, M Vishnu Vardhan Reddy, Ch Tharun Reddy and G Vijendar.	E3S Web of Conferences 391, 01 (2023), ICMED-ICMPC 2023	The input video is converted into frames, preprocessed using filtering and contrast enhancement techniques. Object detection is performed using YOLOv8, followed by motion estimation with the DS algorithm and sliding window processing for weapon detection.	This research focuses on weapon detection in surveillance videos using the YOLOv8 and PELSFDCNN models. The proposed method enhances accuracy by addressing challenges like motion blur and weapon concealment.
2.	Weapon Detection and Alert System using YOLO Deep Learning Technique to Avoid Crimes and Theft, Tejaswini M	IRJMETS, Volume:06/Issue: 06/June-2024	The weapon detection system employs the YOLO (You Only Look Once) deep learning algorithm for real- time detection of weapons in video feeds. Key steps include defining object classes, preparing a labeled dataset, preprocessing images, selecting a pre-trained YOLO model, and fine-tuning it for specific weapon detection tasks.	This system enhances security by automatically detecting firearms or knives in public spaces and alerting authorities through audible signals and notifications. It captures images upon detection to provide visual evidence for further investigation and is designed to operate effectively in various environments such as airports, schools, and public events.
3.	An Enhanced Weapon Detection System using Deep Learning, Sivakumar Murugaiyan	Conference Paper · May 2024 DOI: 10.1109/ICNWC60771.2024.10537568	The methodology utilizes the VGGNet architecture in Keras with TensorFlow, trained on a custom dataset of around 4,000 images across seven weapon categories. The model	The research highlights the urgent need for automated weapon detection systems to enhance security against rising criminal activities, featuring real-time detection capabilities for static images,

			achieves a classification accuracy of 98.40	video streams, and webcam input. With a scalable design and a focus on precision, recall, and F1-score, the system aims to provide an effective solution for public safety across various platforms and environments.
4.	Weapon Detection Alerting System, GOUTHAMI SRAVYA, DR.R.S.PONMAGAL , CH.SAI MANOJ	Journal of Pharmaceutical Negative Results ¦ Volume 14 ¦ Regular Issue 03 ¦ 2023	This system detects weapons like handguns using YOLOv4, trained on a custom dataset. The real-time detection system captures images of the weapon and sends an alert to the admin via email.	The paper aims to improve public safety by identifying weapons in CCTV footage using deep learning techniques. YOLOv4 outperforms previous versions in speed and accuracy, making it suitable for realtime applications.
5.	Weapon Detection using Artificial Intelligence and Machine Learning, Bhagyashri Deore, Pallavi Dhakane, Shaziya Khan, Prof. S. V. Mahale	IJARSCT, Volume 3, Issue1, November 2023	The methodology involves utilizing convolutional neural networks (CNNs) with SSD and Faster RCNN algorithms for automatic weapon detection, employing two datasets: one pre-labeled and another manually labeled. The process includes data preprocessing, feature extraction, and real-time detection to balance accuracy and speed in identifying weapons from video feeds.	The research focuses on enhancing security through an automatic weapon detection system that analyses live video streams to classify and detect firearms, aiming to reduce false positives and improve public safety. The study emphasizes the importance of a diverse dataset and effective machine learning techniques for successful implementation in real-world scenarios.
6.	Weapon Detection Using YOLO V3 for Smart Surveillance System, Sanam Narejo, Bishwajeet Pandey , Doris Esenarro vargas, Ciro Rodriguez , and M.Rizwan Anjum	Hindawi, Mathematical Problems in Engineering Volume 2021, Article ID 9975700, 9 pages	The proposed system uses the YOLO v3 object detection model trained on a custom dataset to detect weapons such as guns and rifles in real-time. The detection framework integrates IP cameras for surveillance and alerts security personnel upon detecting weapons. Additionally, the system records geographical details, including location and time, to provide an actionable response for future incidents.	This paper presents a surveillance system aimed at real-time weapon detection with minimal computational resources. The system leverages deep learning advancements to detect handguns and rifles, alert authorities, and store data for further analysis. With its integration into high-end security robots, the system can improve public safety and prevent mass killings.

Table 1. Literature Survey of Existing Project

Objective

GuardVision aims to revolutionize security measures through advanced weapon detection using computer vision and deep learning techniques. The project's scope encompasses the development of a robust, real-time weapon recognition system capable of processing various input formats and delivering prompt alerts.

- Multi-modal Input Processing: Develop a system that efficiently handles image, video, and live webcam inputs, ensuring versatility in surveillance applications.
- Enhanced Detection Accuracy: Utilize state-of-the-art deep learning models, specifically YOLOv8 combined with Convolutional Neural Networks (CNNs), to achieve high-precision weapon detection across diverse scenarios.
- Real-time Performance: Optimize the system to perform rapid analysis of video streams, aiming for near instantaneous weapon identification to enable swift response times.
- Comprehensive Alert Mechanism: Implement a multifaceted notification system incorporating email alerts, SMS notifications, and dashboard alarms to ensure immediate awareness of potential threats.
- Adaptability and Scalability: Design the system architecture to accommodate future enhancements and integration with existing security infrastructures.
- False Positive Reduction: Develop and implement advanced algorithms to minimize false alarms while maintaining high sensitivity to genuine threats.
- Privacy-Conscious Design: Ensure the system adheres to privacy regulations and ethical considerations in public surveillance.
- User-friendly Interface: Create an intuitive dashboard for security personnel to monitor and respond to alerts efficiently.
- Performance Metrics: Establish and track key performance indicators such as detection accuracy, processing speed, and system reliability.
- Continuous Learning: Implement mechanisms for ongoing system improvement through periodic retraining with new data and user feedback.

By achieving these objectives, GuardVision seeks to set a new standard in automated weapon detection, contributing significantly to public safety and security management.

Computer Vision

Computer vision is a branch of artificial intelligence that empowers computers to interpret and understand visual information from the world, mimicking the human visual system. It encompasses the development of algorithms and systems that can process, analyze, and derive meaningful insights from digital images and videos. At its core, computer vision involves various tasks such as image acquisition, processing, feature extraction, object detection, and scene understanding. The field leverages advanced technologies like machine learning, deep neural networks, and image processing algorithms to achieve its goals. Applications of computer vision are widespread, ranging from facial recognition and autonomous vehicles to medical image analysis and quality control in manufacturing. Despite challenges like handling diverse lighting conditions and complex scenes, computer vision continues to advance rapidly,pushing the boundaries of machine perception and enabling innovative solutions across numerous industries.

Yolov8 Architecture

YOLOv8 architecture represents the latest evolution in the YOLO (You Only Look Once) family of object detection models. It features a streamlined design that integrates a CSPDarknet backbone, Feature Pyramid Network (FPN) neck, and decoupled heads for classification and

bounding box regression.

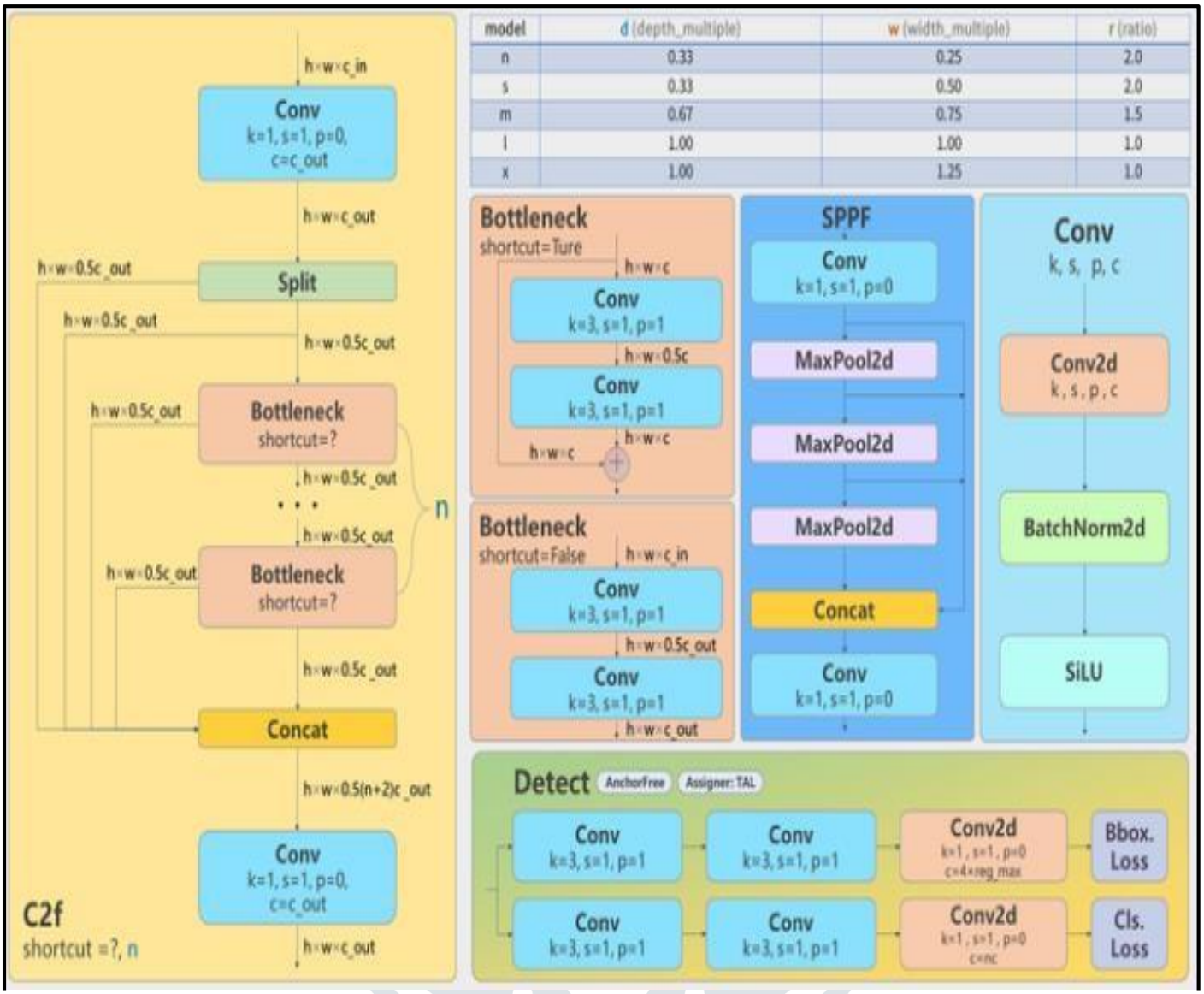

Fig 1. YOLOv8 System Architecture

This advanced structure allows YOLOv8 to process images in a single forward pass, enabling real-time object detection with improved accuracy and efficiency compared to its predecessors.

- Input Processing: The architecture begins with a flexible input layer, accommodating various image sizes crucial for GuardVision's multi-input approach (images, videos, webcam feeds).
- Backbone: YOLOv8 employs a sophisticated CSPDarknet backbone, extracting hierarchical features efficiently from the input, which is vital for detecting weapons of different sizes and types.
- Neck: The architecture incorporates a Feature Pyramid Network (FPN) neck, enhancing GuardVision's ability to detect weapons across multiple scales within surveillance footage.
- Head: YOLOv8's decoupled head design allows for specialized processing of classification and regression tasks, improving GuardVision's accuracy in weapon identification and localization.
- Multi-scale Feature Fusion: The architecture leverages connections between different scales,

enabling GuardVision to robustly detect both small (e.g., handguns) and large weapons (e.g., rifles) in varied environments.

• Mosaic Augmentation: This data augmentation technique, visible in the preprocessing stage, enhances GuardVision's ability to detect weapons in diverse contexts and lighting conditions.

• Loss Functions: The architecture employs specialized loss functions for classification and regression, fine-tuning GuardVision's weapon detection capabilities.

• Non-Maximum Suppression (NMS): This postprocessing step helps GuardVision eliminate duplicate detections, ensuring clean and accurate weapon alerts.

• Output Layers: The final layers provide class probabilities and bounding box coordinates, enabling GuardVision to precisely locate and identify weapons in the monitored area.

Proposed System

GuardVision represents a cutting-edge fusion of computer vision and security technology, designed to revolutionize weapon detection in various environments. This innovative system leverages a multi-tiered approach, beginning with versatile input handling that accommodates static images, video files, and real-time webcam feeds. The preprocessing stage employs advanced techniques like filtering and contrast enhancement to optimize visual data for analysis. At its core, GuardVision utilizes a customized YOLOv8 model,
fine-tuned on an extensive dataset of weapon imagery, enabling rapid and accurate detection of diverse threat objects. To minimize false alarms, the system incorporates a novel dual-verification process, combining the YOLOv8 output with a specialized CNN classifier. This ensemble approach significantly enhances detection reliability across varying conditions.
Upon positive identification, GuardVision activates a comprehensive alert protocol, simultaneously dispatching SMS notifications, emails, and triggering audio alerts on a centralized security dashboard. This multi-channel notification system ensures swift response to potential threats, drastically reducing reaction times in critical situations. The intuitive dashboard interface provides security personnel with real-time visualizations and detailed incident logs, facilitating informed decision-making. By seamlessly integrating

advanced AI algorithms with practical security measures, GuardVision sets a standard in automated surveillance, offering an unparalleled tool for enhancingsafety and threat prevention.

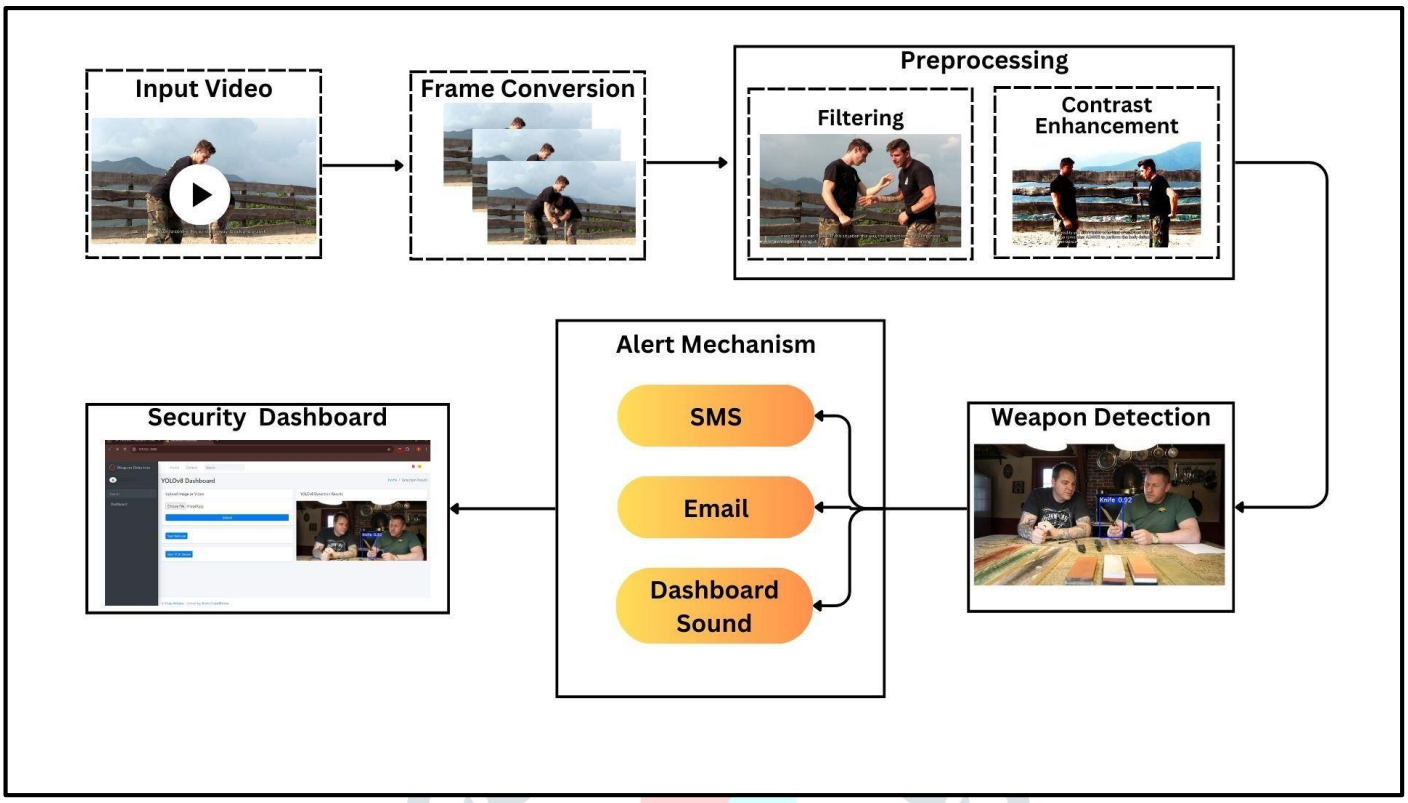

Fig 2. Proposed System Block Diagram

Limitation Of Existing System

The limitations of existing security systems include:

1. VGG-16 Limitations:

• High Computational Load: VGG-16 has a large number of parameters, which leads to slower detection and more resource consumption.

• Not Suitable for Real-Time Detection: Due to its slower processing speed, it's not ideal for live webcam-based detection.

• No Alert Mechanism: VGG-16 lacks an integrated alert system, making it unsuitable for real-time threat notification.

Measures	VGG-16	ResNet-50	YOLOv5	Proposed System
Accuracy	89.75%	93.7%	90%	96%
Precision - Recall	89.71%	76.48%	90.20%	93%
Precision- Confidence	92.84%	96.50%	96.55%	97%
Loss	6.38	2.7	0.9	0.52

Table 2. Comparison of Existing Model

2. ResNet-50 Limitations:

- Degradation Issues: In deeper layers, ResNet models can suffer from vanishing gradients, which may affect the detection accuracy in specific cases.
- Less Effective in Complex Object Detection: For tasks like weapon detection in crowded or unclear environments, its performance might drop.
- No Alert Mechanism: Like VGG-16, ResNet-50 does not include an alert system, making it less suitable for immediate threat response.

3. YOLOv5 Limitations:

- Requires Fine-Tuning for Specific Tasks: YOLOv5 may need extensive fine-tuning and training with specific datasets to ensure high precision in weapon detection tasks.
- Limited Alert Mechanism: While YOLOv5 can trigger alerts, it only supports email notifications, which may not be sufficient for real-time threat response in urgent situations.
- Performance vs Newer Models: YOLOv8 has surpassed it in terms of accuracy and precision, making it slightly less competitive for state-of-theart tasks.

4. YOLOv8 (Proposed System) Limitations:

- Complexity and Resource Demand: YOLOv8 is resource-intensive, so a robust system is required for real time processing, especially with live webcam feeds.
- Training Data Sensitivity: The model's performance can vary depending on the quality and diversity of the training data. Inadequate training data might reduce its effectiveness in detecting weapons under various conditions.

Dataset & Result

DATASET: A lack of a consistent dataset for weapon identification and recognition prompted the development of a distinct dataset consisting of 3302 weapon photos sourced from the internet. In order to assure the effectiveness of detecting and identifying real-life weaponery, the downloaded photographs were meticulously chosen based on their high quality and varied perspectives. An essential component of the pre-processing stage entailed minimizing extraneous elements from every weapon image. An individual analysis was conducted, utilizing several computer tools, to improve the quality and relevancy of images. After creating individual photographs. Each weapon class was considered individually, they were collected and arranged into a dataset. The dataset consisted of monochromatic photographs depicting assault rifles, hunting rifles, knives, handguns, and revolvers. The Python programming language was used to convert each image to grayscale format and resize it to dimensions of 144 × 144 pixels. The photos have been classified according to their respective weapon classifications and arranged accordingly.

Weapon Class	Number of Images
Knife	1109
Pistol	1105
Rifle	1088

Table 3. Dataset used for model training.

Confusion Matrix Analysis

A confusion matrix is a tool used to assess the performance of classification models by comparing predicted labels with actual ones. Each row represents the instances of a predicted class, while each column represents the true class. The diagonal elements indicate the number of correct predictions for each class, whereas the off-diagonal elements show misclassifications. In this matrix, four classes are evaluated: Knife, Pistol, Rifle, and Background. The diagonal values reflect correct predictions, such as 128 for Knife, 85 for Pistol, and 169 for Rifle. Misclassifications, like 16 cases where Knife was predicted as Pistol, are shown in the off-diagonal cells. The matrix highlights areas where the model performs well but also where it struggles, particularly with distinguishing between Knife, Pistol, and Background classes.

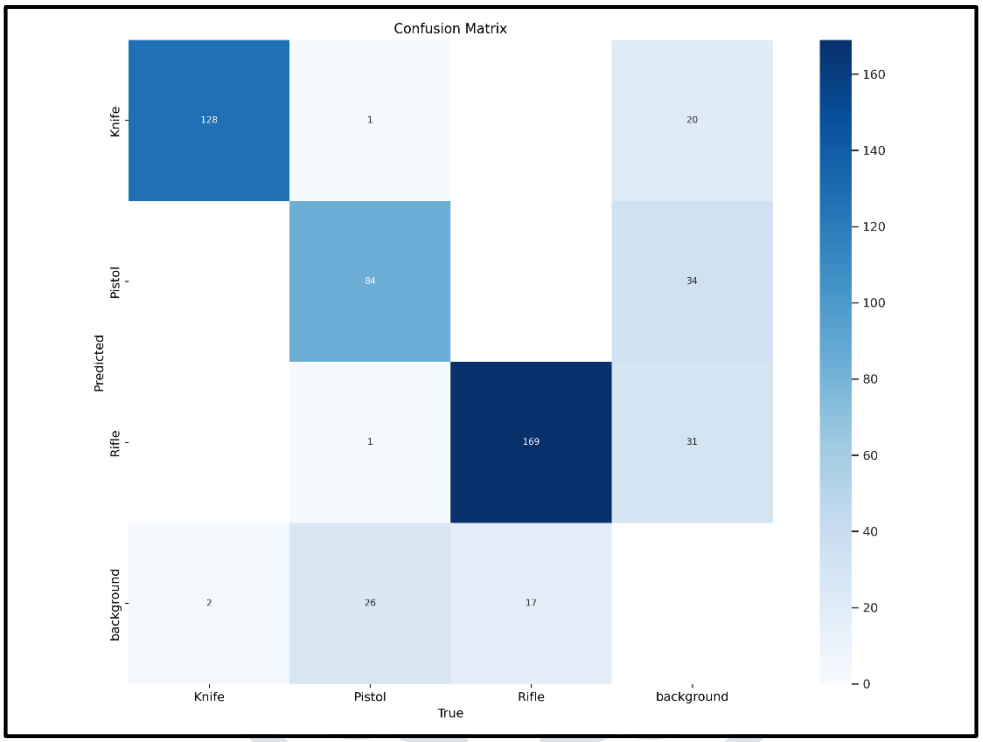

Fig 3. Confusion Matrix of Model

Result

The GuardVision system was tested in a controlled environment using image, video, and live webcam streams to detect weapons. The detection results and alert mechanism functioned as expected across all input types. Below is an overview of the results:

- Weapon Detection Accuracy: The system accurately detected various types of weapons, with real-time identification of objects like pistols. In the example shown in the screenshot (Figure X), a pistol is detected with a confidence score of 0.91. The bounding box around the weapon is clearly outlined, showing the model's ability to detect and label the weapon with high confidence.

- Alert Mechanism: Once a weapon is detected, the system triggers an alert in three forms: Email Notification: An email is sent with details of the detected weapon, including time and type of weapon. -SMS Alert: SMS is triggered with a warning message, notifying relevant personnel of the detected threat.

- Dashboard Notification: A visual alert is shown on the system's dashboard (as seen in Figure X), with a message reading "Weapon Detected (Pistol) - Keep eye on situation", which serves as a real-time alert.

- Processing Input: The system seamlessly accepts input in three formats—uploaded images, video, and live webcam feeds. It processes the input through a robust pre- processing pipeline, which prepares the media for weapon detection.

- User Interface: The detection results are visually represented in the Detection View panel, which displays the detected weapon and the corresponding confidence score. The system also allows users to upload images, video files, or connect a live stream (RTSP or webcam) for monitoring purposes.

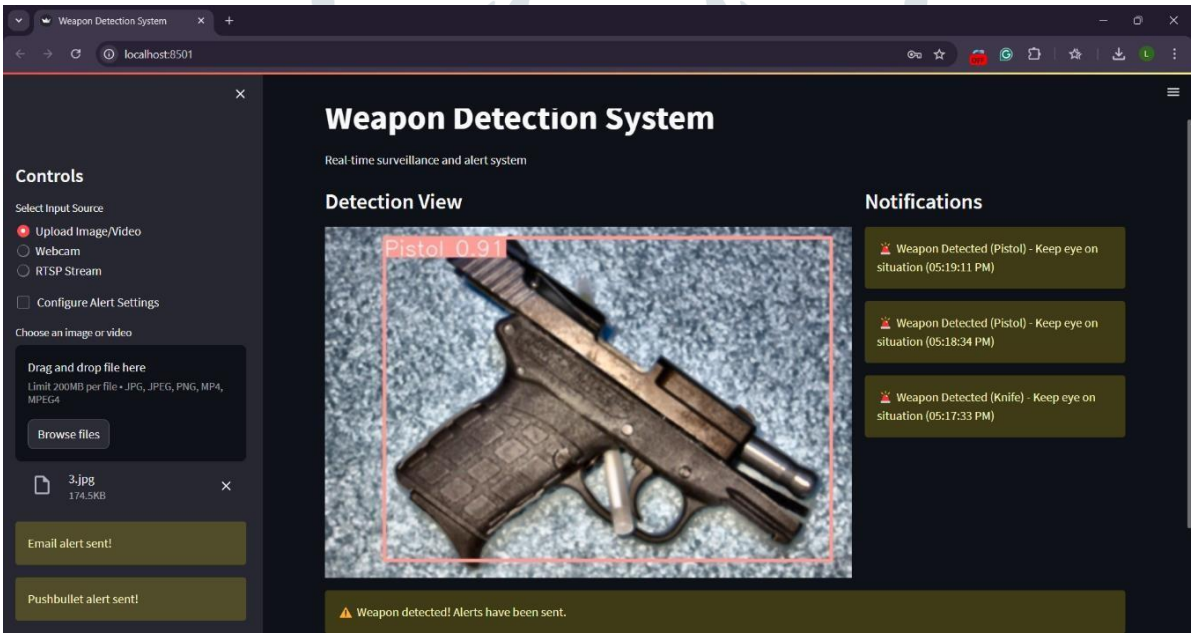

Fig 4. Result of Weapon Detection System.

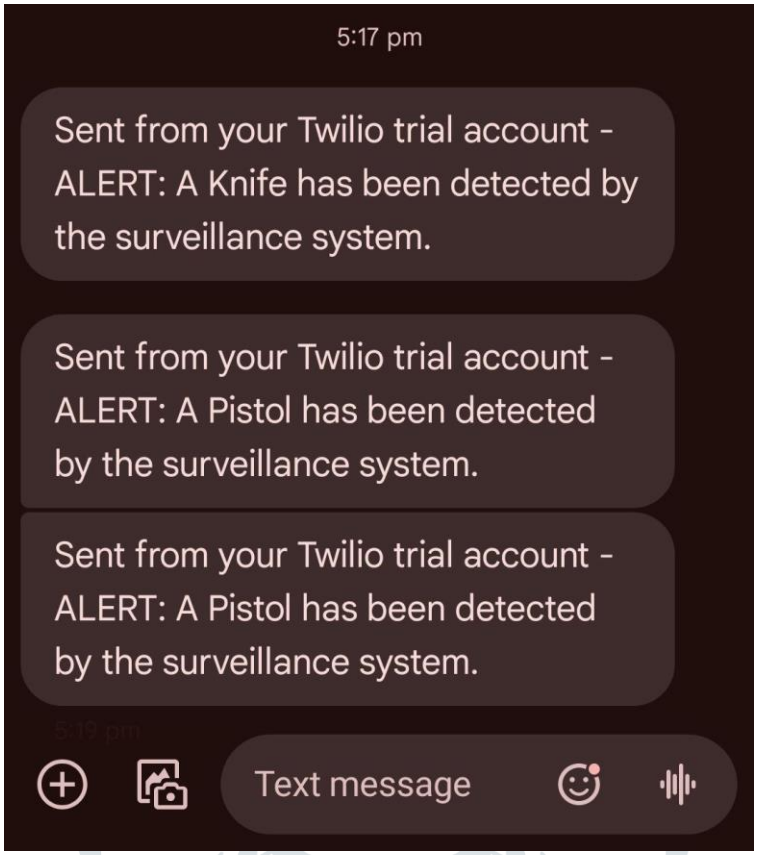

Fig 5. Result of SMS Alert Mechanism System.

Fig 6. Result of Email Alert Mechanism System.

Conclusion

Addressing security concerns in a variety of fields can be done very effectively and efficiently by integrating YOLOv8 into an upgraded weapon detection system. Because of its enhanced accuracy, fast processing speed, and real-time item detection capabilities, YOLOv8 is the perfect tool for weapon identification and localization in intricate settings like public places, airports, schools, and vital infrastructure. Even in chaotic or busy environments, YOLOv8's deep learning-based architecture allows it to detect weapons with extreme precision, including knives, guns, and explosives. Scalability and deployment flexibility are made possible by its ability to run on both high-end GPUs and edge devices, making it suitable for both mobile patrol units and extensive surveillance networks.

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