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Live Monitoring and Smart Threat Detection Using YOLOv8-Based Deep Learning Model

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Abstract

This study introduces a real-time surveillance framework aimed at detecting weapons, with a particular focus on handguns and knives. The approach leverages the YOLOv8 object detection model, chosen for its balance of precision and computational speed. Implemented in Python and integrated through a Flask-based web application, the system provides interactive and user-friendly monitoring options. With a dataset of nearly 4,000 annotated images under varied environments, the framework supports three modes: static image analysis, video stream evaluation, and live webcam monitoring. Experimental evaluation achieved an overall accuracy of 64%, demonstrating its potential for real-world deployment in enhancing security measures.

Keywords: Weapon Recognition, YOLOv8, Deep Learning, Handguns, Knives, Flask, Real-time Detection, Object Recognition, Security Systems.

1. Introduction

The escalation of crimes involving illegal possession and use of weapons poses significant challenges to public safety and national security. Conventional surveillance systems depend heavily on human operators, which often leads to reduced effectiveness due to fatigue, error, or the sheer volume of data to monitor. Advances in Artificial Intelligence (AI) and deep learning have enabled the development of automated surveillance solutions capable of addressing these limitations. Among the models developed, YOLOv8 stands out for its speed and accuracy, making it well-suited for detecting potential threats in real-time across images, videos, and live feeds.

2. Literature Review

Numerous studies have explored intelligent weapon detection approaches. Raturi et al. proposed ADoCW, which integrates both thermal and visual imaging to improve detection accuracy of concealed weapons. Bhagyalakshmi et al. demonstrated a firearm detection system utilizing CNNs to generate automated alerts. Lim et al. introduced a handgun detection framework based on deep neural networks, achieving improved precision at multiple scales.

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Yuan and Guo applied VGGNet for weapon classification, reporting an accuracy of 98.4% on multi-weapon datasets. More recently, Navalgund and Priyadharshini experimented with ResNet50 and YOLOv6 for firearm

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surveillance applications. These works collectively highlight the evolution of approaches, though limitations remain in handling dynamic, real-time conditions.

3. Existing System

Earlier efforts in weapon detection primarily relied on CNN-based models such as VGG-Net. While these methods were effective in static image recognition, they lacked the ability to process real-time streams and were often constrained by limited datasets. This restricted their scalability and adaptability in high-risk and complex surveillance environments, which demand more flexible and responsive systems.

4. Proposed System

The proposed framework improves upon prior systems by integrating YOLOv8 for real-time and multi-modal weapon detection. It provides three operational modes: static image detection, video-based analysis, and live webcam monitoring. The backend is supported by Flask, while the frontend interface is developed using HTML, CSS, and JavaScript. The model was trained on approximately 4,000 annotated images of knives and handguns under diverse conditions, achieving a balanced performance with 64% accuracy. This balance makes the system suitable for practical applications where both accuracy and processing speed are critical.

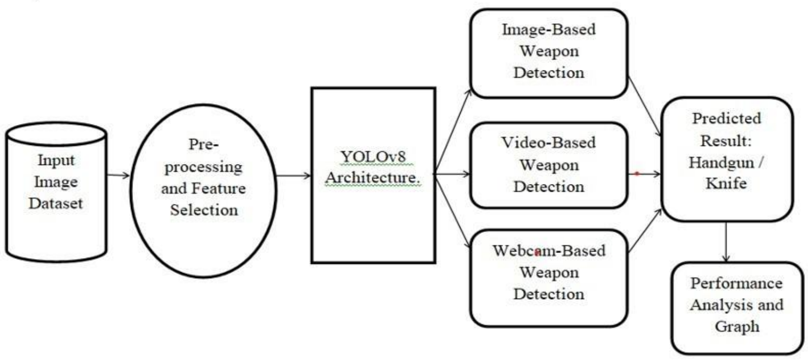

Fig. 1: System Architecture of YOLOv8-Based Weapon Detection Framework

4.1 Features

- **Multi-Modal Recognition:** Supports static images, video feeds, and live webcam streams.
- **User Interface:** Flask-based backend with HTML/CSS/JS frontend for seamless interaction.
- **Dataset:** Trained on ~4000 annotated images of handguns and knives across varied conditions.
- **Performance:** Achieved 64% detection accuracy, balancing speed and reliability.

5. Module Description

The system is divided into functional modules:

1. **Image-Based Detection:** Upload static images for YOLOv8-based recognition.
2. **Video-Based Detection:** Frame-by-frame analysis of video files for weapon presence.
3. **Webcam Real-Time Detection:** Continuous monitoring with live webcam feed.
4. **Training and Evaluation:** YOLOv8 model training with annotated datasets and performance validation.
5. **User Interface:** Flask + HTML/CSS/JS interface with results visualization.
6. **Performance Reporting:** Accuracy plots, logs, and visualization for system monitoring

6. Results

The YOLOv8-based model achieved a 64% detection accuracy across multiple testing conditions. Results showed the framework's ability to balance computational efficiency with reliability. Although the model handled varied environments effectively, challenges were noted in handling limited dataset coverage and occasional false positives. Nonetheless, the results demonstrate the model's readiness for deployment in security applications requiring adaptability and speed.

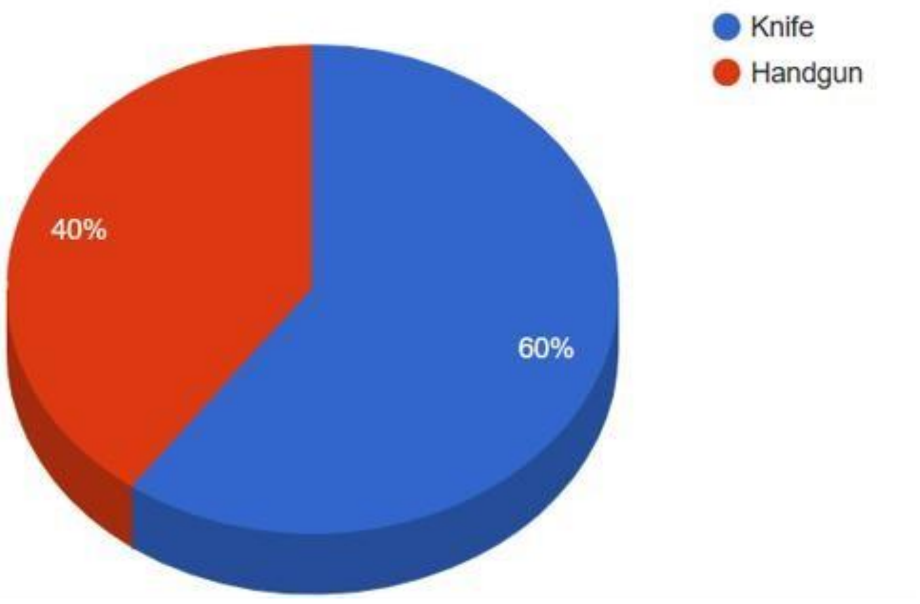

Fig. 2: Resultant Accuracy Distribution (Pie Chart)

The proposed system addresses the shortcomings of traditional surveillance methods by providing:

- Adaptability to dynamic environments.
- Multi-modal input handling.
- A balance between accuracy and computational efficiency.

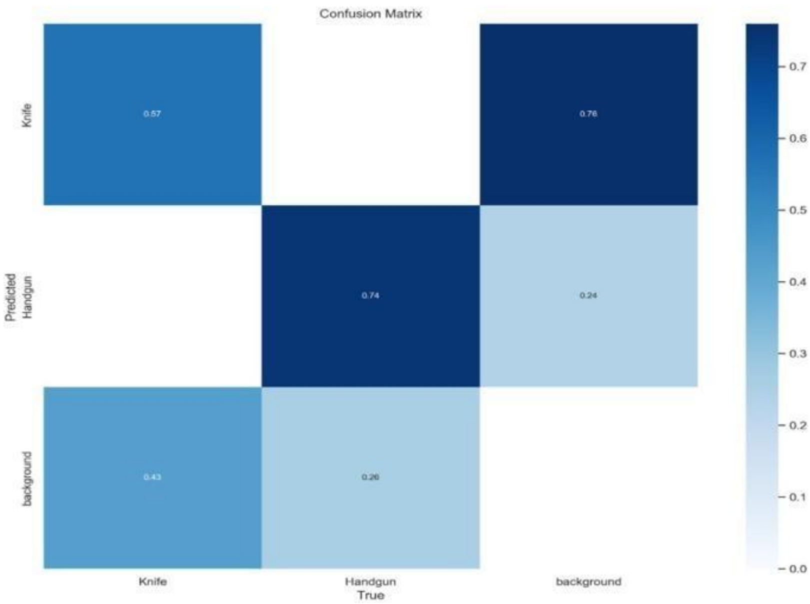

Fig. 3: Confusion Matrix of YOLOv8 Model

Challenges remain, including limited dataset scope, occasional false positives, and computational demand for real-time deployment.

7. Conclusion

This research highlights the effectiveness of YOLOv8 in developing a real-time surveillance system for weapon detection. With 64% detection accuracy across images, videos, and live feeds, the system provides a scalable and efficient solution that addresses the shortcomings of conventional surveillance methods. Future improvements may include expanding the dataset to include a wider range of weapon types, leveraging hardware acceleration to reduce latency, and integrating predictive analytics for proactive threat management.

8. Future Research Directions

- Expanding the dataset to incorporate additional weapon categories.
- Applying predictive analytics to enable proactive threat prevention.
- Utilizing hardware acceleration for improved real-time performance.
- Establishing integration with law enforcement alert systems.

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