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HealthBridge: Enhancing Patient-Centered Care through Digital Health Integration

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ABSTRACT

Effective monitoring has become essential part in the modern day to ensure public safety, particularly in congested areas such as malls, schools, hospitals, and public transit hubs. The continuous human monitoring is a major component of traditional CCTV-based security systems is prone to human mistake, weariness, and delayed emergency response times. In order to detect potentially hazardous things, such knives or firearms, straight from live camera feeds, this study proposes an AI-powered real-time object identification system that makes use of the YOLOv5 (You Only Look Once version 5) deep learning model.

The system is designed to recognize threats with high accuracy and speed. Upon detection of a suspicious object, it immediately triggers an automated alert through visual and audio signals to notify the relevant security personnel. This prompt response can help prevent escalations and allow faster action in critical situations. The model is trained on a custom dataset consisting of various object classes, with a focus on hazardous items. The entire process, from capturing live video to object detection and notification, is done in real-time with minimal latency.

The solution combines front-end interfaces for monitoring and alerting with a robust back-end infrastructure that handles video streaming, model inference, and alert logic This technology greatly increases safety in sensitive areas, reduces reliance on humans, and improves surveillance dependability by automating danger identification through the use of computer vision and deep learning.

KEYWORDS: *YOLOv5, Real-time Object Detection, Surveillance System, Deep Learning, Computer Vision, Threat Detection, Public Safety, Artificial Intelligence, Live Camera Feed, Hazardous Object Detection.*

I. INTRODUCTION

In today's society, monitoring and security are important to preserving public safety in a variety of settings which includes public areas, business buildings, and shopping centers. In order to watch live video and spot possible dangers, traditional CCTV systems depend on human operators. But this manual procedure takes a lot of time, is prone to human mistake, and frequently causes responses to be delayed in urgent situations.

Modern technologies like computer vision and artificial intelligence (AI) are being incorporated into surveillance systems to get beyond these restrictions. Our project, Vision AI, is a real-time object detection system that can automatically recognize suspicious things in live video streams, such as knives or firearms. YOLOv5 (You Only Look Once), a potent deep learning model, enables the system to immediately evaluate video frames and notify security staff in a matter of seconds.

This intelligent surveillance system makes both public and private areas safer and more secure by reducing human error, speeding up reaction times, and taking a proactive approach to managing security concerns in real-time.

II. RELATED WORK

The combination of deep learning and computer vision has led to a rapid evolution in intelligent surveillance systems over the last ten years. Manual monitoring is a major component of traditional surveillance, which frequently leads to human error and a delayed threat response. In order to get over these restrictions, scientists have looked into automated object detection with hybrid models, motion detection techniques, and convolutional neural networks (CNNs). The YOLO (You Only Look Once) model is a notable development in this field that predicts bounding boxes and class probabilities in a single evaluation, enabling real-time object identification capabilities. To efficiently detect motion and follow objects in live video streams, a number of research have also incorporated techniques like optical flow, background subtraction, and frame differencing.

III. PROPOSED WORK

- Traditional systems depend on manual monitoring, prone to errors and inefficiency.
- Object detection using CNNs enables automatic identification of objects in video feeds.
- YOLO model offers real-time performance with high accuracy.
- Optical flow and background subtraction help in motion-based object tracking.
- Hybrid systems combining detection and tracking improve surveillance quality.
- Research shows AI-based alert systems reduce response time and improve public safety.

IV. PROPOSED RESEARCH MODEL :

Fig.1 System Architecture

The diagram shows how a **system architecture** diagram for a real-time threat detection system using YOLOv5 object detection.

1. **Live Camera Feed**: The system continuously captures video from a live camera source.
2. **YOLOv5 Object Detection**: The video feed is processed using the YOLOv5 model, which is a real-time object detection algorithm.
3. Based on detection results, the system branches into two paths:

- **Hazardous Object Identified**: If a hazardous or dangerous object (e.g., weapon, fire, etc.) is detected.
- **No Threat Detected**: If no potentially harmful object is detected.

4. If a hazardous object is found, the system proceeds to:
   - **Generate Real-Time Alerts**: Alert mechanisms (e.g., notifications, alarms, messages) are triggered to inform relevant personnel or systems.

V. PERFORMANCE EVALUTION

Performance Testing

Test Case ID	Metric	Test Condition	Result
PT-001	Object Detection Speed	Process 60 FPS video stream	✅ 95% frames processed in real-time
PT-002	Model Accuracy	Test detection accuracy on different objects	✅ 85% accuracy achieved
PT-003	System Scalability	Handle camera inputs simultaneously	✅ Live streams processed without lag
PT-004	CPU & Memory Usage	Stress test with continuous processing	✅ CPU utilization remained under 70%

Fig.2 Performance Testing

This table represents the **performance testing results** of **VISION AI**.

Analysis of Results:

- **PT-001** confirms that the system efficiently handles high-frame-rate video input, making it suitable for real-time applications.
- **PT-002** validates the detection accuracy across multiple object types, showing reliable classification performance.
- **PT-003** demonstrates scalability, indicating the system can support multiple camera feeds without performance degradation.
- **PT-004** assures resource efficiency, with CPU usage staying below the 70% threshold during extended processing.

These results validate the Vision AI system's performance, reliability, and scalability for deployment in real-time surveillance scenarios.

VI. RESULT ANALYSIS

A number of important criteria, such as alert response, inference speed, and detection accuracy, were used to assess the Vision AI system's performance. To evaluate the system's resilience and effectiveness in detecting potentially dangerous items like knives and guns from live video feeds, tests were conducted in both controlled and real-world settings.

1. Detection Accuracy

The YOLOv5 model achieved a high precision rate in detecting dangerous objects across various lighting conditions and backgrounds. The model was trained on a custom dataset consisting of hazardous object images, yielding the following performance metrics:

- **Precision:** 93.6%
- **Recall:** 91.2%
- **F1-Score:** 92.4%
- **mAP@0.5:** 94.7%

These results demonstrate the model's effectiveness in minimizing both false positives and false negatives, ensuring reliable detection in real-time applications.

2. Real-Time Performance

One of the core strengths of YOLOv5 is its ability to process video frames at high speed. On average, the system processed **30–45 FPS (frames per second)** on an NVIDIA GPU-enabled setup, making it suitable for real-time surveillance.

3. Alert System Responsiveness

The alert mechanism was able to trigger visual and audio notifications **within 1 second** of object detection, ensuring immediate response capabilities. This rapid feedback loop is critical for security personnel to act quickly in emergency situations.

4. Environment Adaptability

Testing in different public environments (e.g., malls, classrooms, lobbies) showed that the system maintained consistent performance. Dynamic conditions such as occlusion, partial visibility, or crowd density had a limited impact on accuracy.

VII. CONCLUSION

The Vision AI system demonstrates a robust and effective approach to enhancing public safety through automated real-time object detection. By leveraging the YOLOv5 deep learning model, the system successfully identifies hazardous objects such as knives and firearms from live camera feeds with high accuracy and low latency. The automated alert mechanism ensures that security personnel are promptly notified, reducing the reliance on continuous human monitoring and significantly improving response times during potential security threats.

Through extensive testing, the system achieved:

- 95% real-time frame processing capability,
- 85% model detection accuracy,
- Stable performance under simultaneous camera streams,
- Efficient resource usage with CPU load maintained under 70%.

These results affirm the system's potential for real-world deployment in environments such as shopping malls, schools, hospitals, and transportation hubs.

VIII. REFERENCE

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