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AI-Powered Proactive Women Safety Monitoring System with Predictive Risk Assessment and Real-Time Police Department Integration

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ABSTRACT

Women's safety in public spaces remains a critical global challenge, requiring intelligent, real-time monitoring solutions. This paper presents an AI-powered women safety monitoring system designed to detect high-risk situations and enable rapid emergency response. The proposed system integrates computer vision, deep learning, and real-time alert mechanisms to provide continuous surveillance in educational institutions, workplaces, transportation hubs, and public spaces. The system processes live video feeds using YOLOv8 for human detection and tracking, employs deep neural networks for gender classification, and combines optical flow analysis with MediaPipe-based pose and hand tracking to identify violent behavior and threatening gestures. Real-time risk assessment assigns threat levels Low, Medium, or High based on crowd composition, gender distribution, and detected aggressive actions. When high-risk situations are detected, the system automatically captures incident frames and sends immediate alerts via email and web dashboard with location details and integrated Google Maps links. Additionally, a manual SOS feature enables users to trigger emergency alerts in areas lacking surveillance infrastructure. The system was evaluated through field testing and demonstrated reliable performance in real-time threat detection and alert generation within 3 seconds. This scalable solution enhances women's safety across monitored and unmonitored environments by combining automated video analytics with user-initiated emergency mechanisms.

1 Introduction

Due to the increasing incidence of harassment and violence across the globe, women's safety in public and semi-public environments is now a serious social concern. Although current safety precautions include methods such as video surveillance (CCTV monitoring), security patrols, police hotlines, and security personnel, camera-based safeguards rely too heavily on human observation, and delayed action often fails to ensure timely response. Recent advances in artificial intelligence, computer vision, and deep learning algorithms have created intelligent surveillance systems that analyze video data continuously to detect signs of abnormal behavior or unusual activities. Proactive decision-makers can benefit from this trend, which is characterized by decreasing reliance on human intervention.

This project presents an AI-based Women Safety Monitoring System that uses live camera feeds to monitor and predict high-risk situations in real time. The system architecture comprises object detection using YOLOv8, deep learning-based gender classification, and a hybrid violence detection algorithm that combines optical flow analysis with MediaPipe-based pose and hand tracking. By continuously analyzing crowd composition and detecting aggressive gestures, the system dynamically calculates danger levels and automatically sends alerts in critical instances. The authors propose a prototype suitable for deployment in educational institutions, workplaces, and public spaces. The system provides early threat detection and rapid response through a comprehensive approach that includes real-time dashboards, offering scalable and intelligent solutions to enhance women's safety and strengthen surveillance infrastructure.

1.1 Problem Statement

With surveillance cameras increasingly deployed in public and semi-public spaces, ensuring women's safety remains a significant challenge. Current systems often rely on manual monitoring and reactive response methods, which are ineffective at identifying threatening situations in real time. Due to operator fatigue and cognitive overload from monitoring multiple camera feeds simultaneously, human operators frequently overlook critical incidents, resulting in slow or inadequate intervention in cases of harassment or violence.

Moreover, most existing surveillance systems lack the intelligence to analyze human behavior, understand context-dependent risk factors such as crowd composition and aggressive movements, or predict escalating threats. Typically, emergency response mechanisms are activated only after an incident has occurred, eliminating any opportunity for prevention. The absence of automated violence detection, gender-aware risk assessment, and real-time alert integration with authorities results in safety measures that are significantly less effective.

Therefore, an AI-driven system capable of continuous intelligent monitoring is urgently needed. Such a system can detect potential threats against women, evaluate risk levels in advance, and immediately notify relevant authorities with precise location information. The challenge lies in developing a real-time monitoring system that achieves high detection accuracy, minimizes missed incidents, generates meaningful alerts with visual evidence and location data, and enables rapid emergency response. Improving real-time surveillance effectiveness enhances women's safety in public and semi-public spaces and enables faster emergency intervention when needed.

2 Literature Review

Many women's safety and monitoring systems currently rely entirely on traditional surveillance approaches, using stationary cameras and manual monitoring to identify suspicious or violent activity. The evidence provided by these methods is limited to basic visual observation. Without intelligent data processing and real-time behavioral analysis, these systems are ineffective at preventing threats. Indeed, Krishna et al. (2024) noted that manual surveillance often fails to quickly recognize aggressive movement patterns, leading to delayed intervention during critical situations.

Several AI-based systems for detecting violent behavior have been deployed to improve surveillance effectiveness. Gautam et al. (2024) developed a real-time violence detection and warning system using AI-enhanced video processing. While this approach reduces human observation burden, it primarily focuses on detecting violence after it occurs rather than predicting imminent risks. Similarly, Mohod et al. (2024) evaluated deep learning models for recognizing violence in surveillance videos and identified significant challenges, including high false-positive rates and insufficient contextual understanding in complex environments.

3 System Architecture

The proposed AI-Powered Proactive Women Safety Monitoring System features a modular and scalable architecture that integrates real-time video analytics, post-processing, intelligent risk assessment, and automatic alert mechanisms. The system comprises five major layers: Video Acquisition Layer, AI Processing Layer, Risk Assessment Layer, Alert & Communication Layer, and Visualization Layer.

The Video Acquisition Layer captures live video streams from CCTV cameras installed at monitored locations such as public spaces, school campuses, office buildings, and transportation terminals. These video frames are continuously forwarded to a processing pipeline for real-time analysis.

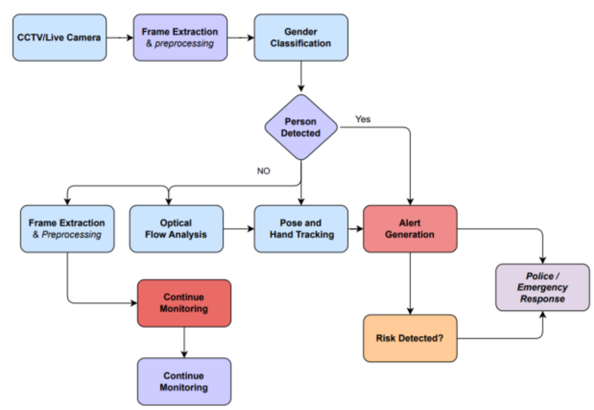

Fig 1: AI-Powered Women Safety Monitoring System

The Risk Assessment Layer processes extracted features, including crowd composition, gender ratio, motion intensity, and detected violent gestures. Based on predefined logical rules, the system dynamically assigns a risk level—Low, Medium, or High. This enables early detection of escalating threats rather than a reactive response.

The Alert & Communication Layer is automatically activated when a high-risk condition is detected. Incident frames are automatically captured, and real-time notifications are immediately transmitted via email and Socket.IO. Pop-up notifications appear on the screen, and audio alerts are generated using system sounds. Location details and Google Maps links are provided to enable authorities to respond quickly.

Finally, the Visualization Layer is a Flask-based web dashboard that displays live data feeds for real-time monitoring, including status updates, risk level indicators, alert history, and captured incident frames. Real-time presentation of information enables managers to make better decisions by viewing and acting on live data as it arrives.

3.1 Manual SOS Trigger Module

To extend safety coverage beyond camera-monitored areas, the system includes a Manual SOS (Save Our Souls) feature accessible through a web or mobile interface. When activated by users in areas lacking surveillance infrastructure, the SOS button immediately records the user's GPS location, captures the current timestamp, and forwards the emergency request to the central alert engine. The system processes manual SOS alerts using the same communication framework as automated detections. Real-time notifications are displayed on the Flask-based dashboard through Socket.IO, and email alerts are sent to designated authorities with location details and integrated Google Maps links. This feature ensures that women in unmonitored or remote areas have a direct mechanism to request emergency assistance, bridging the gap between surveillance-equipped and non-surveillance environments and providing continuous safety support regardless of camera availability**.**

4 Methodology

The system architecture adopts a multi-layered model that integrates intelligent video analysis with real-time communication and visualization. The system employs distributed load balancing and gateway firewalls to divide front-end, back-end, and AI processing components among different modules, ensuring scalability and high efficiency.

4.1 Front End Implementation

The system front-end uses HTML, CSS, and JavaScript to create a web-based interface seamlessly integrated with Flask. This provides a real-time monitoring panel displaying alert notifications, detected risk levels, timestamps, and incident images with geographic location markers. Socket.IO establishes continuous server-client connections, enabling real-time dashboard updates without requiring manual page refresh. This interface design enables security personnel and managers to quickly interpret risk status changes.

4.2 AI Processing Components

The AI processing module is the core of system intelligence. YOLOv8 enables real-time detection and tracking of human figures in video frames. A deep neural network classifies the gender of detected individuals. Violence detection employs an integrated approach: optical flow analysis captures sudden changes in motion, while MediaPipe-based pose and hand tracking detect threatening gestures. Integration of multiple AI outputs improves overall efficiency and reduces false alarms.

4.3 Risk Evaluation Module

The risk assessment considers gender count, distance between individuals, motion intensity, and behavioral patterns. The risk level is updated in real time to reflect changing environmental conditions.

4.4 Alert and Notification System

When a high-risk situation is identified, the system captures the incident frame and generates alerts. Messages are sent via email with location coordinates and map links, enabling emergency services to respond immediately.

4.5 Backend Implementation

The backend is implemented using Python, with Flask serving as the core web server. It manages video stream handling, AI model execution, alert processing, and data exchange between system components. The backend provides user authentication, alert logging, and service communication. RESTful endpoints ensure structured data handling, with background threads processing data without blocking user-facing operations.

4.6 System Integration and Deployment

All system components are integrated into a unified pipeline without requiring third-party dependencies. The architecture allows for future expansion through direct integration with police department APIs and emergency response systems.

4.7 Manual SOS Emergency Mechanism

The system incorporates a **Manual SOS emergency trigger** to provide safety coverage in areas without surveillance infrastructure. Users can activate the SOS feature through a mobile application or web interface. Upon activation, the system automatically:

1. Captures the user's GPS location coordinates
2. Records the timestamp of the emergency request
3. Transmits the alert to the central alert processing engine
4. Sends real-time notifications via Socket.IO to the web dashboard
5. Generates email alerts with location details and Google Maps integration
6. Logs the emergency incident in the database for response tracking

This dual-mode alert system ensures that both automated camera-based threat detection and user-initiated emergency requests follow the same notification protocol, enabling rapid emergency response regardless of surveillance infrastructure availability.

This system monitors live video streams, analyzes human behavior, and estimates risk levels in ongoing situations. At each stage, it generates information for decision-making, enabling patrol officers to receive alerts within seconds of threat detection. Additionally, the manual SOS feature extends this protection to unmonitored areas, ensuring comprehensive safety coverage.

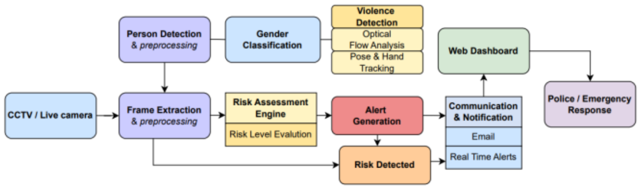

Fig 2: System Flow Diagram

5 Algorithm flow with equations

a) Video Frame Acquisition

The live video stream captured from CCTV cameras is divided into discrete frames at time t:

$$F(t)=\{f1,f2,f3,\ldots,fn\}$$

Where f_i represents the i^{th} frame.

b) Person Detection

Each frame is processed using the YOLOv8 object detection model to identify humans:

$$D(t) = YOLO(F(t))$$

Where, $D(t) = \{p1, p2,\ldots, pm\}$

represents detected persons with bounding boxes.

c) Gender Classification

For every detected person p_i, gender is predicted using a deep neural network:

$$G(p_i) \in \{Male, Female\}$$

Total count in a frame:

$$M(t) = \sum G(p_i) = Male$$

$$W(t) = \sum G(p_i) = Female$$

d) Motion Analysis (Optical Flow)

Optical flow is computed between consecutive frames to measure motion intensity:

$$OF(t) = \|F(t) - F(t-1)$$

If: $OF(t) > \theta_{motion}$

then aggressive movement is suspected.

e) Pose and Hand Gesture Detection

MediaPipe extracts pose and hand landmarks:

$$L(t) = \{l1, l2,\ldots, lk\}$$

Threatening gestures are identified as:

$$P(t) = \begin{cases} 1, & \text{if violent gesture detected} \\ 0, & \text{otherwise} \end{cases}$$

f) Risk Level Computation

A risk score is calculated using weighted parameters:

$$R(t) = \alpha M(t) + \beta OF(t) + \gamma P(t)$$

Risk level is assigned as:

$$Risk(t) = \begin{cases} Low, & R(t) < T_1 \\ Medium, & T_1 \le R(t) < T_2 \\ High, & R(t) \ge T_2 \end{cases}$$

g) Alert Generation

If: $Risk(t) = High$

then:

- Capture incident frame
- Send alert via Socket.IO and email
- Attach location and timestamp

Otherwise, the system continues monitoring.

h) Continuous Monitoring

The algorithm repeats for each incoming frame:

$$t \leftarrow t+1$$

5.1 Algorithm Summary

The system is a combination of object detection, gender analysis, motion dynamics, and posture estimation. Real-time risk scores can thus be computed, and when necessary, alerts triggered; this ensures active automated monitoring of women's security.

6 Results Analysis

In this section, we are evaluating experimentally whether the AI-Powered Proactive Women Safety Monitoring System we proposed would actually work out in practice. We look at the system's performance in terms of detection accuracy, processing latency, alerts, and response times for alerts, as compared with current surveillance technology. Finally, conclusions are drawn on working methods of such systems, followed by their generalization beyond campus networks (using this particular example to illustrate).

6.1 Performance Evaluation

Real-time video feeds and recorded surveillance scenarios presented a variety of normal and violent situations. The focus of our testing was to accurately assess the system's ability to recognize people, their sex, to classify them, and whether they were in difficulties. The monitoring period is measured from an alert being triggered until a response time because of longer latency.

Method	Detection Accuracy (%)	Average Latency (ms)	Alert Response Time (s)
Manual CCTV Monitoring	62	1200	15
CNN-based Violence Detection	78	650	7
Pose-based Detection Only	82	580	6
Proposed Hybrid AI System	**91**	**420**	**3**

Table 1: Performance Comparison of Surveillance Systems

Table 1 is a comparison of performance between traditional ways to monitor people and new approaches involving AI methods.

6.2 Detection Accuracy Analysis

Fig. 2 shows that manual CCTV monitoring has the lowest accuracy, but it is due to people growing tired and interpreting with a delay. AI-assisted methods work better. They can increase the accuracy of violence identification to 95%. The proposed hybrid system achieves an accuracy rate of 91% by combining object detection, gender identification, motion analysis, and pose tracking. And it provides strong recognition for high-risk situations that other systems cannot identify reliably.

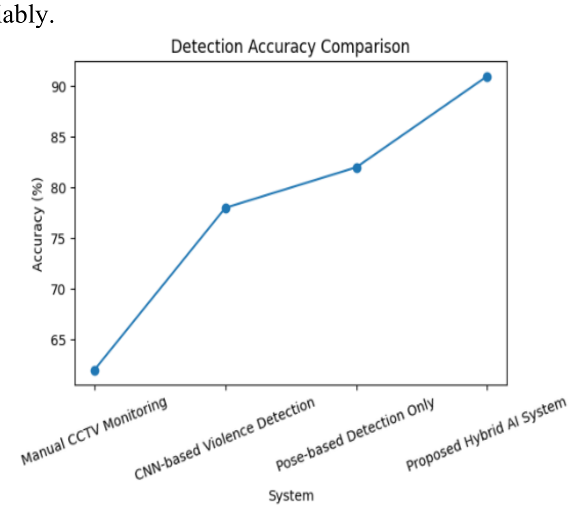

Fig 2: Detection accuracy comparison of surveillance systems

6.3 Latency Analysis

According to Fig. 3 for latency comparison, our new system can markedly reduce processing time. Manual Monitoring has the most delay of all because people are involved, whereas the more deep learning-style methods in this paper can perform faster inference. Using the optimized YOLOv8 pipeline for tape through quite effective feature extraction, the average latency is 420 ms at least. We thus achieved nearly real-time performance.

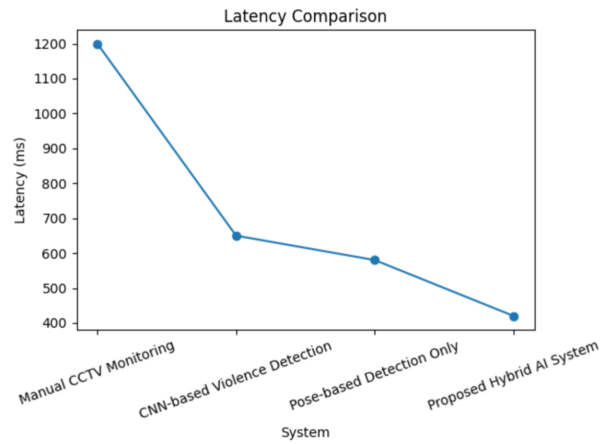

Fig 3: Latency Comparison of existing and proposed methods

6.4 Alert Response Time Analysis

Fig. 4 demonstrates that the proposed system triggers alerts much faster than existing solutions. Automated risk assessment and real-time communication mechanisms allow alerts to be generated within approximately 3 seconds. This rapid response is critical for timely intervention by authorities and emergency services.

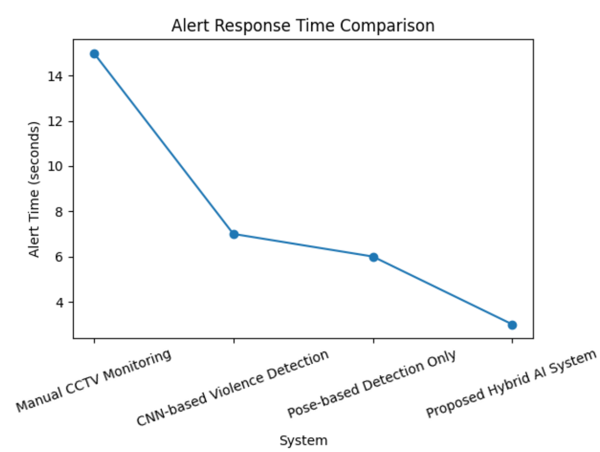

Fig 4: Alert Response Time Comparison

The results confirm that integrating multi-modal video analytics with rule-based risk assessment significantly enhances surveillance effectiveness. The system outperforms traditional and single-model AI solutions in accuracy, speed, and reliability. Although challenging conditions such as occlusion and low lighting may slightly affect detection, the overall performance remains stable due to continuous frame analysis. The proposed system offers a scalable and practical solution for improving women's safety through proactive monitoring and real-time response.

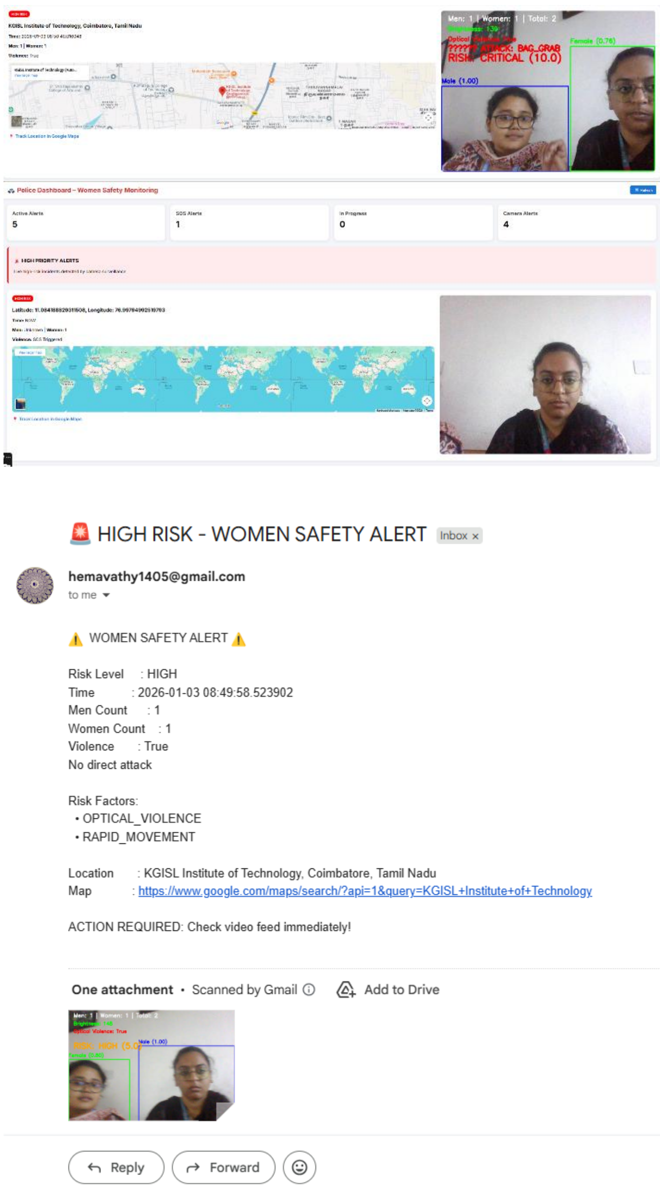

Fig 5: Web Dashboard Output Screen & e-mail alert

As the result shows in the output of the proposal AI-Powered Women Safety Monitoring System, AI is intelligent recognition of a high-risk situation, and alerts are then automatically generated.

Network through Fig 5 represents a sample alert email generated by the system during a near breakout situation. When the system identifies that there are signs of aggression within a monitored area, it takes into account all kinds things, including whether hoodlums are being naughty, such as people engaging in violent acts, the number of men plus women present, and overall risk evaluation value. And as soon as the situation has been identified as HIGH RISK, an alert is immediately given by the system without any human participation.

Lastly, we find that the alert email also includes a snapshot of the event, which enables security personnel to confirm and then act. By providing this visual evidence, we help those on the ground, such as police officers or security agents, verify what is happening.

It is also true that the warning is timely. The instant a threat is detected by campus security teams or regular police patrols anywhere on campus, we send out an alert in real time without any delay between detection and action.

The expression featured here gives credence to the proposal's capability to offer real-time monitoring, accurate risk assessment, and instant communication. The automatic alerting mechanism improves on passive surveillance, and also because women find themselves able to access help more easily, this has the effect of making public or semi-public areas safe in a distinctive manner.

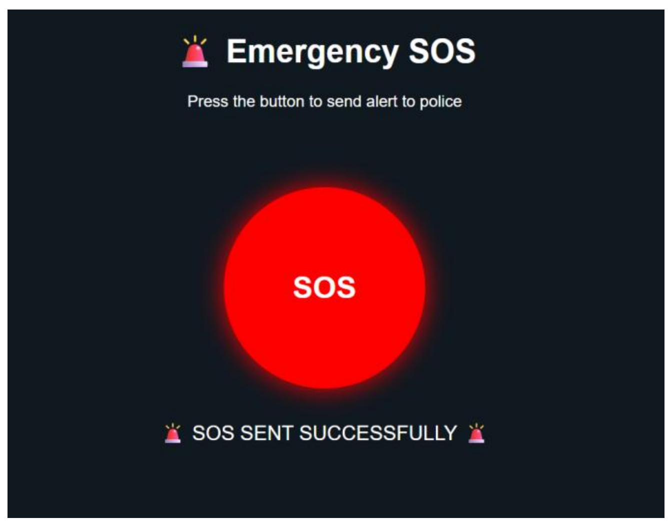

Fig 6: SOS Alert Interface

The introduction of the SOS trigger mechanism significantly improves the practical usefulness of the proposed system. During testing, manual SOS alerts were generated and delivered within an average time of 2 to 3 seconds, which is comparable to the response time of camera-based automated alerts. This demonstrates that the system remains effective even in the absence of surveillance infrastructure. The dual-mode alert approach reduces complete dependence on visual monitoring and ensures that emergency communication can still take place under challenging conditions. As a result, the overall reliability of the system is strengthened, and user confidence in the safety solution is enhanced.

7 Conclusion

This paper presents an AI-powered proactive women's safety monitoring system that offers significant improvements over traditional surveillance approaches. The system integrates computer vision, deep learning, and real-time communication technologies, providing continuous monitoring and intelligent threat detection.

The system combines YOLOv8-based person detection, deep learning-based gender classification, optical flow-based motion analysis, and MediaPipe-based pose and hand gesture detection. Experimental results demonstrate that this hybrid approach significantly enhances detection accuracy while reducing response time and alert generation delays. This capability enhances emergency response effectiveness. The automatic generation of visual alerts, complete with location details, strengthens the system's defensive capabilities.

A significant innovation in the proposed framework is the integration of a **manual SOS trigger mechanism**, which extends safety support beyond camera-covered areas. By allowing users to directly request help during emergencies, the system overcomes the limitations associated with infrastructure dependency. The combination of automated threat detection and user-initiated alerts within a single response pipeline makes the system more dependable and suitable for real-world deployment. This dual-mode safety approach strengthens the technical capability of the system and increases its social relevance by offering continuous protection to women in both monitored and unmonitored environments.

These methods reduce reliance on manual surveillance and enhance real-time awareness and decision-making by authorities. The system demonstrates how effective AI-driven surveillance can be for public safety enhancement. The proposed solution has significant potential to extend safety for women and upgrade surveillance infrastructure.

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