© April 2025 | IJIRT | Volume 11 Issue 11 | ISSN: 2349-6002

Women Safety Analytics– Protecting Women from Safety Hazards

Dr. K. Ram Mohan Rao[1], Mohammed Imran[2], Sai Kiran Kasarla[3]
Department of Information Technology Vasavi College of Engineering Hyderabad, India

***Abstract*—Women's safety is a major social issue. As women nowadays are more than ever worried about being victimized, assaulted, or finding themselves in dangerous locations, this project aims to examine, anticipate, and stimulate action through data analysis, AI, and machine learning. The relevant system evaluates different data points ranging from past occurrences of crimes to socioeconomic contribution through continuous surveillance and geographic location. It performs real time analysis through data received from CCTV. The machine learning algorithms derive correlations and obtain detection to evaluate risk and recognize real time events like rapid movements. Through evaluation of past incidents and contributions of situations, zones can be identified that reflect how dangerous a zone is for women.**

***Index Terms*—CNN-Based Gender Classification; deepSORT-Based Person Tracking; MiDaS Monocular Depth Estimation; Nominatim; Optical Flow Analysis; Spatiotemporal Hotspot Analytics; Real-Time Video Processing; YOLOv8**

I. INTRODUCTION

Conventional safety measures tend to focus only on reactive methods, responding to events only after they have taken place. This project centers on harnessing these technologies to evaluate and enhance women's safety with real-time surveillance and analytics *[1],* through the integration of various datasets like historical crime data, social indicators, and location-based variables, the system detects risk zones, identifies events, and creates actionable insights. The objective is to equip authorities and citizens with real-time information so that data-driven decisions can be made to improve safety, allocate resources optimally, and develop safer environments.

Key functionalities include live threat detection such as violence or distress via surveillance analysis, risk identification from safety scores, and hotspot analysis to analyze areas of potential danger. These insights aid law enforcement, and local communities in making evidence-based decisions and taking proactive measures towards safety. *[1], [2].*

This project seeks to address the following critical questions:

1. How can we automate the process of CCTV monitoring to detect crimes against women *[1]*?
2. Where can this system be effectively deployed to maximize its impact *[1]*?
3. How can real-time alerts during crimes enable officials to take immediate action, making the process preventive *[7]*?
4. How can hotspot analysis provide factual insights into crime distribution, helping allocate resources more effectively *[4] , [6]*?

Fig 1: The illustration depicts an AI-powered surveillance system on a college campus detecting a potential women safety threat.

Expected Solution: Women safety analytics should have the following features

1. Person detection in given frame [9].
2. Gender Classification: Enumerate the count of men and women in the scene [2].
3. Proximity of men and women [11], [12].
4. Rapid Movement Detection [13].
5. Risk analysis for alert generation [14].
6. Detection of hotspots based on the previous alerts [4], [6].

II. RELATED WORK

Perceptions of Women's Safety in Transient Environments and the Potential Role of AI in Enhancing Safety:

This research shows the gender differences and their opinions in travel behavior throughout India the following are the findings from this paper, 57% of women mainly depend on walking for their daily activities compared to just 22% of men, and 43% of men traveling by motorized transport, while just 12% of women do this. The survey highlights how safety is an important consideration 4 for women in their transport choice, with 54% of those asked choosing the safest mode of transportation to prevent crime and harassment. And, 42% of the respondents responded the CCTV monitoring as the strongest safety feature, highlighting how AI-based crime hotspot examination and facial recognition can help upgrade preventive systems. [1].

Human Gender Classification Using Machine Learning

This research paper highlights some of the machine learning techniques of gender classification, this includes feature extraction methods such as SIFT which is and classification methods such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). The research reveals that SVM performed better than CNN in most instances, with an accuracy of up to 98% on live image data, making it the highest performing method for gender classification. Nevertheless, the paper points out some primary challenges like misclassification due to facial expression changes and image quality issues, which can compromise real-world performance. In future directions, also has a challenge of using in CCTV footages where quality is not that good [2].

Crime Hotspot Detection Using DBSCAN Algorithm

To determine crime hotspots, the DBSCAN algorithm is applied in this research to apply the crime analysis to identify incidents through density-based clustering. Here clustering vs non - clustering was studied and clustering approach gave better accuracy on dataset The research demonstrates how DBSCAN can effectively cluster incidents through density, separating high-crime and low-crime areas by processing vast volumes of spatial crime data. The findings provide important data to law enforcement agencies that enables resources to be better allocated and targeted crime prevention strategies developed. Hence this analysis of past crime data is helpful to better allocate resources [4].

Crime Mapping and Forecasting Using Geospatial Techniques

This study addresses the use of location-based information in predicting and mapping criminal activities. Through an examination of geographic trends and patterns, the research highlights the role of Geographic Information Systems (GIS) in studying crime distribution. The authors explore different methodologies in crime mapping and prediction, indicating how spatial analysis can be beneficial to law enforcement agencies in planning strategically, resource allocation, and proactive crime prevention. Hence this study was helpful in our hotspot analysis implementation in our project [6].

Towards Robust Monocular Depth Estimation: Mixing Datasets for Zero-shot Cross-dataset Transfer

This research investigates how combining multiple datasets improves monocular depth estimation. Current depth datasets are limited by size, diversity, and incompatible annotations, making it difficult to train effective models. The authors introduce a new loss function to handle depth scale differences across datasets, enabling their integration during training. They also introduce a large dataset from 3D movies, which includes diverse, dynamic scenes to address gaps in existing datasets. The combined approach achieves state-of-the-art results, reducing errors by up to 22%. These findings suggest that using diverse datasets and careful training strategies can improve depth estimation for real-world applications like autonomous driving and robotics. Future work could explore even larger datasets or better integration methods [11].

Monocular Depth Estimation Based on Deep Learning: An Overview

This work gives an introduction to deep learning-based monocular depth estimation, which estimates depth from a single image. Most traditional techniques such as stereo matching or structure-from-motion take more than one image and result in sparse depth maps, whereas deep learning can make dense depth estimation from one image possible. The work classifies methods into three categories: supervised (based on labeled depth data), unsupervised (based on geometric constraints from video), and semi-supervised (integrating labeled and unlabeled data).

Important datasets such as KITTI and NYU Depth are mentioned, and also evaluation measures such as RMSE and relative error. Challenges such as scale ambiguity in unsupervised and the requirement of large labeled data in supervised approaches are pointed out by the paper. In general, deep learning has tremendously improved monocular depth estimation but still faces hurdles in generalization and efficiency [12].

III. METHODOLOGY

Components Used	Description	Model & Dataset
Person Detection	To detect people in real time by generating bounding boxes and confidence scores. [9], [1]	YOLOv8(nanoversion,COCOtrained)
Gender Classification	For prediction on detected person regions, outputting gender labels and probability. [7],[2], [5]	Custom MobileNet CNN
Object Tracking	Provides consistent ID assignment for reliable real-time tracking across frames. [10]	DeepSORT
Depth Estimation	For monocular depth estimation that generates depth maps for 3D distance estimation. [11], [12]	MiDaS (Small Version)
Rapid Movement Detection	Computes optical flow between consecutive frames to measure speed and direction, detecting rapid movements indicating potential violence. [13]	Farnebäck Optical Flow
Risk Assessment	Combines factors such as proximity, rapid movement, and historical incident data to calculate a risk score and trigger alerts. [14]	Rule-Based Algorithm
Hotspot Analysis	Clusters historical and real-time incident data to visualize crime hotspots and guide resource allocation. [4], [6]	DBSCAN Clustering + GIS Mapping (via Folium)
Location Detection	Uses public IP-based geocoding and Nominatim to automatically detect location (latitude, longitude, and descriptive address).	IP Geolocation (IP-API & Nominatim)
Incident Logging	Log incident details (timestamp, location, gender counts, risk score, etc.) for hotspot analysis.	SQLite Database

Table 1: Detailed summary of the key components.

Our planned Women Safety Analytics project includes real-time processing of video with machine learning to measure and act preventively in unsafe situations. As given in the table there are following components used in the project. The project is organized into major components: for person detection, a COCO dataset–trained YOLOv8 is deployed on every video frame to generate bounding boxes, average Depth in a Bounding Box is mean(depth_map[y1:y2, x1:x2]) and confidence scores for detected individuals [9], [1], achieving high detection accuracy even in crowded scenes; for gender classification, a custom MobileNet CNN model processes the detected person regions to classify gender [2], [5] by outputting labels with corresponding probabilities per individual; for tracking, deepSORT assigns consistent IDs to individuals in consecutive frames using appearance and motion cues, thus ensuring temporal consistency in tracking movements [10]. Both 2D and 3D distance measurements are utilized, where the Euclidean distance between centers of person bounding boxes is computed as a preliminary measure where pixel_distance can be found by eq(1).

$$\text{Pixel distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \; - - - - \rightarrow eq(1)$$

Where, $(x_1, y_2), (x_2, y_2)$ are coordinates of center of two bounding boxes of two people.

Estimated real world distance is given by eq(2).
meter_per_pixel =
scale_factor * average_depth $--\rightarrow eq(2)$

Then real world distance is computed by eq(3).
real_world_distance =

$$\text{pixel\_distance} * \text{meter\_per\_pixel} ----\rightarrow eq(3)$$

MiDaS is used for generating accurate depth maps from a single image input [11], [12]. Rapid movement is detected by examining consecutive frames with optical flow, where Optical Flow Magnitude (Farnebäck) is computed by eq(4).

$$\text{flow\_magnitude} = \text{sqrt}(u^2 + v^2) ---\rightarrow eq(4)$$

where ‘u’ is the x-component of velocity and ‘v’ is the y-component of velocity.

This measures movement speed and direction to identify sudden, aggressive, or unusual behavior [13]. A rule-based risk assessment system combines factors such as proximity, rapid movement, gender distribution, and other features to generate a risk score and trigger warnings when a specified threshold is exceeded [14]. The alert system integrates SMTP for email and the Twilio API for SMS, providing notifications with details such as location (accompanied by a Google map link), timing, and risk type, thus enabling anticipatory responses from security personnel. Incident logging is maintained in an SQLite database that records each incident with time, location, and risk score for trend analysis and auditing, while hotspot analysis compiles historical and recorded data to determine geographical clusters of high risk using spatial analysis and clustering methods [4] and offers insights for long-term resource allocation and preventive measures [6].

The figure 2 below shows the flow of video data through preprocessing, detection, and gender classification layers, and displays how processed results feed into storage components and real-time dashboards for monitoring.

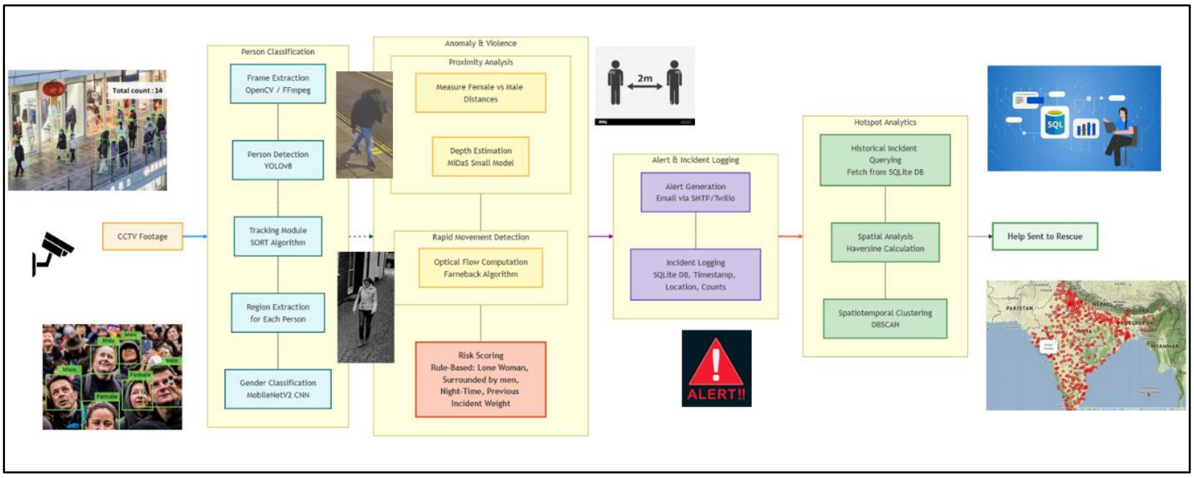

Fig 2: Architecture Diagram

Advantages:

Our system offers real-time performance and efficiency by providing instant detection, tracking, and risk analysis, which facilitates timely interventions even during high video frame rate processing. In addition, proactive alerting, logging, and hotspot analysis features generate alerts via email and SMS, enabling prompt responses by security personnel, and perform analytics on recorded and historical incident data to identify high-risk areas for better resource deployment and preventive action.

IV. EXPERIMENTAL SETUP

Testing was performed on a Windows PC with an Intel i7 processor, 8 GB of RAM, and an NVIDIA GPU to support deep learning inference acceleration. External devices like webcams or CCTV sourced videos were utilized to supply live input scenarios. The deployment utilized Python 3.8+, utilizing libraries like OpenCV for video processing and PyTorch for model inference. Deep learning models (YOLOv8, MiDaS Small, and custom MobileNet CNN) were combined using pre-trained weights and fine-tuned where appropriate. Live video feed and recorded video feed input data included both of these types, with the former containing multiple scenarios within public spaces. Person detection accuracy was evaluated through checking bounding box correctness and detection confidence in dynamic video frames. Depth estimation from MiDaS Small was checked by comparing computed depth maps with anticipated relative distances in test cases. Tracking pipeline (deepSORT) was checked based on its correctness to keep ID assignment consistent between consecutive frames.

Real-Time Performance: We measured in terms of processing speed (frames per second) to verify that the system would function well in real-time. Utilized qualitative video inspection and quantitative standards (e.g., confidence of detection, risk score thresholds) to assess the effectiveness of the system.

V. RESULTS

The project showed good performance when evaluated against ground truth annotations and through an ablation study. YOLOv8 reliably detected people, while our proprietary MobileNet CNN consistently identified gender correctly. An ablation study confirmed the critical role of depth estimation via MiDaS with Euclidean measurements enabling efficient 3D distance estimation. DeepSORT maintained real-time tracking, and optical flow analysis effectively detected rapid movements that could indicate violence. Automatic alerts delivered via email and SMS, along with detailed incident recording and hotspot analysis, further validated the system's overall efficacy in comparison with ground truth data. The following figure shows a real time dashboard where live CCTV feeds undergo person detection, gender classification, distance measurement, rapid movement detection and finally risk score is identified. The following figure displays a clustered visualization of incidents on the India map, where each cluster represents multiple nearby incidents, clicking on a specific location reveals detailed information about the incident.

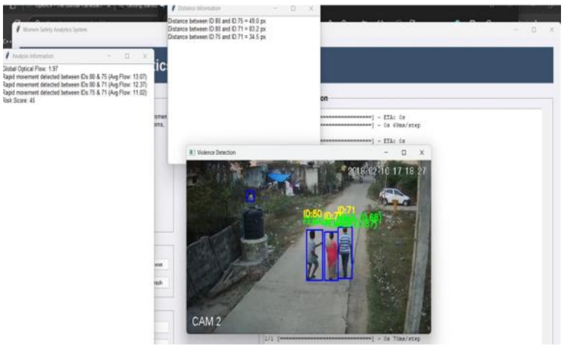

Fig 3: Analyzing real time footage

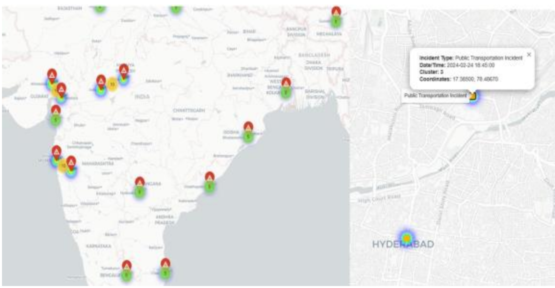

Fig 4: Hotspot Analysis with clustering

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

The combination of AI and video analytics can improve women's safety in public environments like public transport, hospitals, college campuses, and office buildings. Real-time monitoring systems with features such as live detection, facial recognition, and behavior analysis have been effective in detecting and preventing potential threats. But there are many challenges: reduce biases in training data can underestimate AI model performance, and privacy reasons from wide surveillance which needs a balance between security and individual rights. Ethical issues also need to be addressed through open policies and cooperation among policymakers, and community leaders. Whereas earlier research has tackled individual elements systematically ranging from gender classification and crime hotspot identification to depth estimation the literature highlights a key gap in bringing these technologies together into a smooth, real-time system that transcends practical constraints in suboptimal surveillance environments.

B. Future Work

Wrapper Implementation Around CCTV Cameras. Create an independent module that can be integrated with existing CCTV systems smoothly. Edge Device and Cloud-Based Server-Side Computing. Run light-weight instances of the analytics pipeline on edge devices to make the first detection and tracking close to the data source. Other Enhancements and Integration. Broaden the system to include more sensors (audio, thermal imaging) for a more detailed context in threat assessment.

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