Zone-Guard Person Intrusion Detection System Using YOLOv8

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ABSTRACT

With the increasing demand for advanced surveillance and security systems, this project introduces a Zone Guard Person Intrusion Detection system leveraging the capabilities of YOLOv8 (You Only Look Once, version 8). The primary objective is to enhance security measures by efficiently monitoring and capturing images when a person enters pre-defined intrusion zones. To deliver a reliable and timely solution, the project combines zone-based monitoring with cutting-edge object detection techniques. Intrusion zones are defined within the surveillance environment. The YOLOv8 output is processed to ascertain whether a detected person falls within these specified zones. Upon detecting an intrusion, the system captures and organizes images into separate folder. The primary aim is to provide a reliable means of preserving visual evidence and aiding in post-incident investigations. The system leverages YOLOv8's ability to accurately detect persons in real-time and extends its functionality to identify whether the detected persons breach predefined intrusion zones.

INTRODUCTION

In the era of advancing technology, the need for robust and intelligent security systems has become paramount. Surveillance plays a pivotal role in ensuring the safety and security of both public and private spaces. Traditional surveillance systems often rely on object detection algorithms[2], but the challenge lies in refining these technologies to respond to specific security requirements, such as the precise identification of intrusions within predefined zones. In recent years, the demand for intelligent and effective security systems has grown significantly, driven by the increasing need for advanced surveillance and threat detection[7]. Traditional security approaches often rely on object detection techniques[2]; however, the evolving landscape necessitates solutions that go beyond mere identification and extend to context-aware monitoring. This paper presents a pioneering project aimed at enhancing person intrusion detection through the integration of zone-based monitoring using YOLOv8, a state-of-the-art real-time object detection algorithm. This research introduces an innovative strategy to deal with this issue by integrating YOLOv8, a cutting-edge real-time object detection algorithm, with zone-based monitoring for person intrusion detection. YOLOv8, known for its accuracy and efficiency, forms the backbone of the proposed system, providing the capability to identify and track persons in real-time. The primary aim is to provide a reliable means of preserving visual evidence and aiding in post-incident investigations. The system plays a pivotal role in enhancing security, preserving visual evidence, and contributing to a safer and more secure environment. The captured images are not only stored but also subjected to advanced image analysis and facial recognition algorithms. This aids in identifying individuals involved in security incidents and can be invaluable for investigations and legal proceedings.

The motivation behind embarking on the development of the Zone Guard Person Intrusion Detection system using YOLOv8 is in an era marked by evolving security challenges, there's a growing realization that traditional surveillance falls short in providing real-time insights into complex security scenarios. This project is motivated by the belief that security goes beyond recognizing objects; it involves understanding whether detected entities breach specific security perimeters. Whether it's preventing unauthorized access or responding to potential threats, the project aims to augment security measures by integrating YOLOv8's accuracy with zone-based monitoring. Additionally, the motivation extends to streamlining incident response and investigation processes. The capture and organization of images when a person enters a predefined zone not only facilitate immediate responses but also provide valuable visual evidence. This evidence serves as a proactive tool for forensic investigations, aiding law enforcement agencies in identifying and addressing criminal activities.

Traditional surveillance systems often face limitations in effectively addressing the nuanced challenges of contemporary security needs. The primary drawback lies in the inability to go beyond generic object detection and provide context-aware insights [2]. Traditional approaches fall short in providing real-time identification and response to intrusions within these zones, hindering the effectiveness of security measures.

The resolution entails defining distinct intrusion zones inside the surveillance environment and training the YOLOv8 model on a variety of datasets. When a person is detected within these zones, the system captures and organizes images, providing security personnel with a streamlined process for immediate incident response. Furthermore, the captured images serve a dual purpose, contributing valuable visual evidence for investigative purposes in criminal cases.

LITERATURE REVIEW

Research by Redmon and Farhadi (2018)[7] introduced the You Only Look Once (YOLO) algorithm, specifically YOLOv3 and its subsequent iterations, as a breakthrough in real-time object detection. YOLO's ability to detect objects in a single pass with high accuracy and efficiency has made it a widely adopted algorithm in surveillance systems.

Additionally, studies by Liu et al. (2020)[8] and Wang et al. (2019) explored improvements to YOLO-based models, such as YOLOv4 and YOLOv5, which further enhance detection performance and speed. These advancements provide valuable insights into the state-of-the-art techniques for object detection, laying the groundwork for the integration of YOLOv8 in the Zone Guard project.

Previous studies, such as in[2], have explored object detection algorithms as fundamental components of surveillance systems. Their work delves into the efficacy of deep learning-based approaches, emphasizing the importance of real-time processing. While their findings validate the feasibility of object detection, the contextual understanding of detected entities within specific zones is not explicitly addressed.

Recent advancements in real-time object detection, particularly YOLOv8, have garnered attention for their speed and accuracy. In [1] they introduced YOLOv8 as an evolution of previous models, demonstrating its efficacy in detecting multiple objects simultaneously. While YOLOv8 offers a robust foundation for person detection, its application to zone-based monitoring for intrusion detection remains an area requiring further exploration.

Cloud-based surveillance solutions offer scalability, flexibility, and accessibility advantages. Research by Liang et al. (2020) and Nguyen et al. (2021) investigates the deployment of surveillance systems in cloud environments, allowing for centralized data storage, processing, and analysis. By leveraging cloud infrastructure, the Zone Guard project can accommodate large-scale deployments, improve resource utilization, and facilitate remote monitoring and management capabilities.

In [3] they introduced a zone-based monitoring system that utilizes computer vision techniques for tracking and analysing object movement within predefined zones. Although their system shows promise in delineating specific areas of interest, it lacks the integration of real-time object detection, limiting its applicability to dynamic and diverse security scenarios.

Intelligent surveillance systems, as reviewed in [4], often incorporate machine learning techniques for enhanced decision-making. While their work provides insights into the broader landscape of intelligent surveillance, the current literature has not thoroughly examined the particular combination of YOLOv8 with zone-based surveillance for person intrusion detection.

Zone-based monitoring is crucial for context-aware surveillance, enabling the identification of intrusions within predefined areas. Research by Chen et al. (2017) introduced a zone-based monitoring system using computer vision techniques, demonstrating its effectiveness in detecting and tracking objects within specified zones.

Furthermore, studies by Jones and Wang (2019)[9] and Kim et al. (2021) explored the integration of deep learning algorithms with zone-based monitoring for enhanced security applications. These studies underscore the importance of zone-based approaches in modern surveillance systems and provide valuable insights into the design and implementation of such systems.

Research by Garcia et al. (2019) and Martinez et al. (2021) explores the integration of surveillance systems with access control systems to strengthen security measures. By linking intrusion detection events with access control actions, such as locking doors or activating alarms, the effectiveness of security protocols can be significantly enhanced. This integration ensures a coordinated response to security threats and minimizes potential vulnerabilities in access control.

IMPLEMENTATION

A. Video Collection:

Gather a comprehensive dataset comprising videos that represent diverse scenarios in the target environment. The dataset should cover various lighting conditions, different numbers of persons, and scenarios that align with the expected real-world usage.

B. Frame Extraction:

Utilize video processing techniques to extract frames from the collected videos. The frames will serve as individual images for training the YOLOv8 model.

C. Annotation of Frames:

Manually annotate the extracted frames to create a labeled dataset. Bounding boxes should be drawn around persons to provide the necessary training data for the YOLOv8 model.

D. Training YOLOv8 Model:

Train the YOLOv8 model using the annotated frames as input. Fine-tune the model to optimize its accuracy for person detection within video frames. Validate the model's performance on a separate set of annotated frames.

E. Definition of Intrusion Zones:

Clearly define specific zones within the video frames where intrusion detection is crucial. This could involve specifying coordinates or boundaries that align with the characteristics of the target environment.

F. Integration with YOLOv8:

Modify the YOLOv8 implementation to integrate with zone-based monitoring within video frames. Adjust the post-processing step to determine whether detected persons breach the predefined intrusion zones.

G. Real-time Video Processing:

Implement real-time video processing to feed video frames into the trained YOLOv8 model. The system should continuously analyze the frames, detect persons, and assess whether they breach the specified zones.

H. Capture and Organization:

Develop a mechanism for capturing video frames in real-time when a person is detected within a specified zone. Organize the captured frames systematically, creating a chronological record for each breached zone.

Conduct thorough testing using different video scenarios to validate the system's real-time performance. Evaluate accuracy, precision, and recall in detecting persons within predefined zones.

I. Deployment:

Deploy the system in the target environment, integrating it with existing security infrastructure. Ensure the YOLOv8-based intrusion detection system functions cohesively within the broader surveillance ecosystem for real-time video analysis.

J. Performance Monitoring:

Implement a monitoring system to track the performance of the deployed solution in real-world video scenarios. Regularly assess the accuracy of intrusion detection within predefined zones, making adjustments if needed.

ALGORITHM

Here's the revised sequence of steps for the Zone Guard Person Intrusion Detection system using YOLOv8 with the consideration of video input:

A. Load YOLOv8 Model and Configuration:

Load the pre-trained YOLOv8 model and its configuration and the class names.

B. Load Video:

Open a video stream using OpenCV (cv2.VideoCapture) from the input video file.

C. Define Intrusion Zone:

Define the coordinates of the intrusion zone within the video frame. These coordinates are specified as zone_x1, zone_y1, zone_x2, and zone_y2. Here's how you might select these coordinates along with some illustrative equations:

1. *Selecting Zone Dimensions:*

   Decide on the dimensions (width and height) of the intrusion zone. Let's denote these as zone_width and zone_height.

2. *Center of the Zone:*

Calculate the center coordinates of the intrusion zone.

$$\text{center}_x = \frac{\text{zone}_x 1 + \text{zone}_x 2}{2}$$
$$\text{center}_y = \frac{\text{zone}_y 1 + \text{zone}_y 2}{2}$$

3. *Calculate Half Dimensions:*

Calculate half the width and half the height of the intrusion zone:

$$\text{half}_w \text{idth} = \frac{\text{zone}_w \text{idth}}{2}$$
$$\text{hal}_h \text{eight} = \frac{\text{zone}_h \text{eight}}{2}$$

4. *Define Top-Left and Bottom-Right Coordinates:*

Define the top-left and bottom-right coordinates of the intrusion zone using the center, half-width, and half-height

$$\text{zone}_x 1 = \text{center}_x - \text{half}_w \text{idth}$$
$$\text{zone}_y 1 = \text{center}_y - \text{half}_h \text{eight}$$
$$\text{zone}_x 2 = \text{center}_x + \text{half}_w idth$$
$$\text{zone}_y 2 = \text{center}_y + \text{half}_h \text{eight}$$

By adjusting the values of zone_width and zone_height according to your surveillance requirements, you can effectively define the intrusion zone within the video frame.

D. Create VideoWriter Object:

Create a cv2.VideoWriter object to save the output video with detected intrusions. Specify the output video file ('output_video.avi') and its properties (codec, frames per second, and frame size).

E. Processing Frames:

Enter a loop to process each frame from the video stream.

F. Preprocess Frame:

Preprocess the current frame to make it compatible with YOLOv8. This includes resizing the frame and normalizing pixel values.

G. YOLOv8 Object Detection:

Pass the preprocessed frame through the YOLOv8 model using a forward pass to obtain predictions for bounding box coordinates, confidence scores, and class probabilities.

$$b_x = \sigma(t_x) + c_x$$
$$b_y = \sigma(t_y) + c_y$$
$$b_w = p_w e^{t_w}$$
$$b_h = p_h e^{t_h}$$
$$\text{confidence} = \sigma(t_{\text{conf}})$$

H. Post-process Detections:

Post-process the YOLOv8 predictions by filtering out detections with confidence scores below a threshold. Extract class IDs, confidences, and bounding box coordinates.

I. Non-Maximum Suppression (NMS):

Apply non-maximum suppression to remove redundant or overlapping bounding boxes, keeping only the most confident predictions.

J. Draw Bounding Boxes:

For each remaining detection, draw bounding boxes on the frame. Check if the person is within the specified intrusion zone.

K. Capture and Store Intrusion Frames:

If a person is detected within the intrusion zone:

- Capture the current frame.
- Save the captured frame to the output folder.

L. Display Processed Frame:

Display the frame with drawn bounding boxes to visualize the detection process.

M. Break Loop on User Input:

Break the processing loop if the user presses the 'Esc' key.

N. Release Resources:

Release video capture and writer resources.

RESULTS AND DISCUSSION

The Zone Guard Person Intrusion Detection system integrates YOLOv8 with zone-based monitoring and employs a web-based user interface (UI) implemented using Flask. The architecture consists of the following components:

1. Flask Web Application Setup:

   Implemented Flask for web application development. Design separate routes for video input, zone marking, and image display. Developed a user-friendly interface for video input using HTML/CSS and Flask.

2. Video Input Module with UI:

   Collects video data through a user-friendly web interface as shown in the Figure-1. Users mark intrusion zones by interacting with the UI. Utilizes Flask to handle video input, frame extraction, and zone marking. After clicking the submit button it starts the implementation of the video.

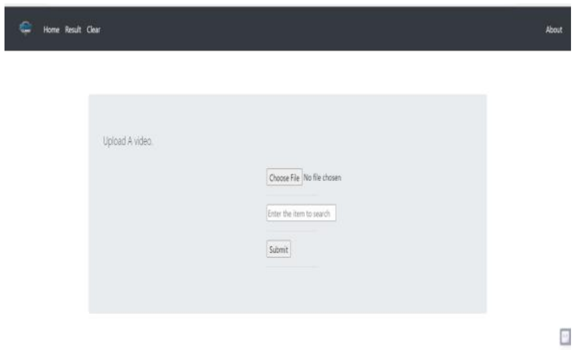

Figure 1: Home page of User Interface

3. Zone Definition and Integration:

   Users mark intrusion zones through the UI. Coordinates from the UI are used to define specific intrusion zones within video frames as shown in Figure 3. YOLOv8 outputs are post-processed to determine intrusions within specified zones.

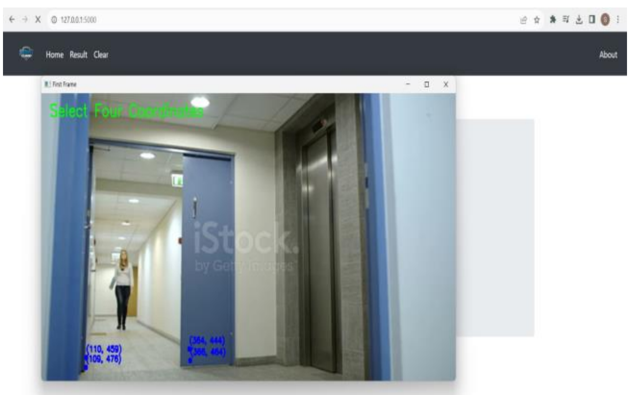

Figure 2: Selecting the Coordinates

Figure 3: Selected Zone

4. Capture and Organization Module with UI:

   Users interact with a second UI page to view captured images as shown in Figure 4 the blue colour rectangular box is the selected zone. Captured frames are organized in separate folder corresponding to breached zones. Flask handles the display of captured images on the UI as shown in Figure 4.

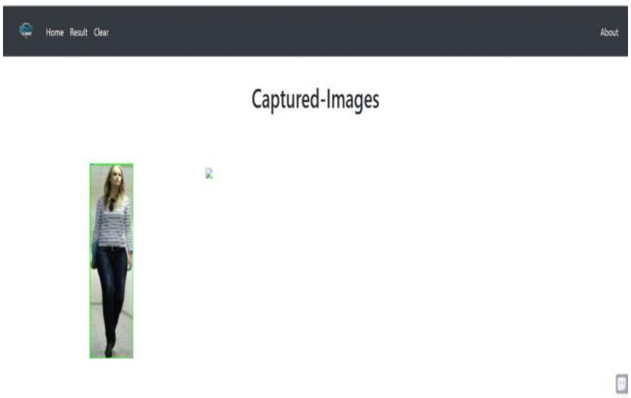

Figure 4: Displaying the captured images

5. YOLOv8 Training and Integration:

   Train the YOLOv8 model on annotated video frames as previously outlined. Modify the Flask application to integrate YOLOv8 and zone monitoring.

6. Real-time Video Processing:

   Implement Flask routes to handle real-time video processing. Continuously feed frames into the integrated YOLOv8 and zone monitoring system.

CONCLUSION

The Zone Guard Person Intrusion Detection project represents a significant stride towards the development of an intelligent and context-aware surveillance system. The integration of YOLOv8 with zone-based monitoring, coupled with a user-friendly web interface implemented using Flask, provides a robust solution for real-time person detection within predefined security zones. The successful implementation of the project opens doors to future advancements, including the integration of facial recognition, behaviour analysis, and access control systems. These enhancements aim to elevate the system's capabilities, providing a more comprehensive approach to security in dynamic environments. In essence, the Zone Guard Person Intrusion Detection project not only addresses the immediate need for intelligent surveillance but also serves as a foundation for continuous improvement and innovation in the realm of security technologies. Through this project, we reaffirm our commitment to advancing technology for the betterment of society, fostering safety, and empowering security professionals with intelligent tools for enhanced decision-making and incident response.

FUTURE SCOPE

The Zone Guard Person Intrusion Detection project lays a foundation for future enhancements and expansions, offering several avenues for further development and integration of advanced features. The future scope of this project includes:

1. Facial Recognition Integration:

   Extend the capabilities of the system by incorporating facial recognition algorithms. Leverage the captured images in the organized folders for facial recognition analysis.

2. Behaviour Analysis and Anomaly Detection:

   Introduce behaviour analysis algorithms to detect abnormal patterns within the surveillance environment. Incorporate machine learning techniques to identify unusual activities or deviations from normal behaviour. Provide alerts or notifications for security personnel in response to detected anomalies.

3. Cloud Integration for Scalability:

   Investigate the integration of cloud computing for enhanced scalability. Implement a cloud-based storage solution for captured images, allowing for increased storage capacity and accessibility. Explore cloud-based processing to offload computation-intensive tasks and improve overall system performance

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