RESEARCH PAPER

REAL-TIME CROWD AND VIOLENCE DETECTION USING YOLOV8 ALGORITHM

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ABSTRACT

The proposed system aims to develop a real-time crowd and violence detection system using the state-of-the-art YOLOv8 algorithm. The system monitors live video feeds to detect sudden increases in crowd density and violent activities, providing real-time alerts for quick intervention. By leveraging the YOLOv8 model's advanced object detection capabilities, the system ensures high accuracy and speed in identifying potential security threats in public areas such as gatherings, events, and surveillance zones. This technology improves public safety by allowing authorities to respond quickly and proactively to incidents. The proposed system works by first collecting and preprocessing data from various sources, followed by training the YOLOv8 model on a curated dataset of diverse crowd and violence scenarios. This model is then integrated with a user-friendly interface that allows security personnel to interact with the system, receive notifications, and take action. Upon detecting an anomaly, the system triggers both an alert sound and an email notification, ensuring immediate attention. The system's ability to track crowd behavior and identify violent actions provides an enhanced security monitoring solution that is scalable and reliable. By combining real-time object detection, crowd density analysis, and violence detection into one integrated system, this project contributes significantly to the field of public safety and surveillance. This approach ensures that the system can handle diverse public safety challenges in various real-world settings.

Keywords: YOLOv8, Crowd Detection, Violence Detection, Real-time Surveillance, Object Detection, Public Safety

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I. INTRODUCTION

Public safety is a crucial concern in modern societies, especially in crowded public spaces such as transportation hubs, stadiums, and marketplaces. The rapid growth of urban populations has led to an increase in public gatherings, necessitating more efficient surveillance systems. Traditional security measures, including human monitoring and static CCTV surveillance, have limitations such as fatigue, errors, and delays in response time.with the advancement of artificial intelligence (AI) and computer vision, surveillance systems have evolved to incorporate automated monitoring. These systems help analyze human movement patterns, detect anomalies, and identify threats more accurately than manual methods. Machine learning models, especially deep learning algorithms, have significantly improved the efficiency of such systems by enabling automated, real-time threat detection.violence detection, in particular, has become a critical aspect of surveillance due to increasing incidents of criminal activities and public disturbances. Traditional surveillance cameras record events, but real-time response is lacking unless a human observer actively watches the footage. Delayed responses to violence and sudden crowd surges can lead to casualties, property damage, and chaos. To address these limitations, AI-driven solutions such as YOLO (You Only Look Once) have been employed for object detection, crowd analysis, and violence recognition. The latest iteration, YOLOv8, provides real-time detection capabilities with improved accuracy and efficiency. This project aims to

integrate YOLOv8 into a real-time monitoring system for public safety applications. By leveraging deep learning and real-time alert mechanisms, this project enhances security and response times in high-risk environments. The integration of automated email notifications and audio alerts ensures that security personnel and authorities can react promptly to potential threats.

II. LITERATURE SURVEY

[1] **Inbavalli A., Jarshini T., and Muralikrishnaa M.** proposed a concept in which an aggressive behavior detection and alert system was created using deep learning techniques. The system processes video feeds in real time to identify instances of aggressive behavior and trigger alerts. It employs Convolutional Neural Networks (CNNs) and

other deep learning algorithms to ensure high accuracy and efficiency. This system enables immediate responses to violence or aggression in public spaces.

"EFFICIENT AGGRESSIVE BEHAVIOUR DETECTION AND ALERT SYSTEM EMPLOYING DEEP LEARNING TECHNIQUES – 2024"

Advantages - The system provides quick response times and high accuracy, helping to prevent violence escalation. By detecting aggressive behavior in real time, it enhances security and safety in public areas.

Disadvantages - The system's performance depends on the quality of the video feed. It may face challenges in highly crowded environments, where detecting individual aggressive actions becomes more difficult

[2] **Sudharson D., Srinithi J., Akshara S., Abhirami K., Sriharshitha P., and Priyanka K.** proposed a concept in which a proactive headcount and suspicious activity detection system was developed using the YOLOv8 algorithm. The system processes live video feeds to estimate crowd sizes and detect unusual behavior in public spaces. By identifying potential security threats in real time, it enables proactive safety measures.

"PROACTIVE HEADCOUNT AND SUSPICIOUS ACTIVITY DETECTION USING YOLOv8 – 2023"

Advantages - The system is highly effective for crowd control and monitoring. It can identify a variety of suspicious activities with high precision, improving public safety.

Disadvantages - The system may face difficulties in highly congested areas, where distinguishing between normal and suspicious behavior becomes challenging.

[3] **Nasir R., Jalil Z., Nasir M., Noor U., Ashraf M., and Saleem S.** proposed a concept in which an enhanced framework for real-time dense crowd abnormal behavior detection was developed using the YOLOv8 algorithm. The system is designed for dense crowd surveillance, identifying abnormal behaviors such as fights or panic in highly packed areas and triggering alerts for timely intervention. It employs data augmentation and advanced tracking techniques to enhance detection accuracy."AN ENHANCED FRAMEWORK FOR REAL-TIME DENSE CROWD ABNORMAL BEHAVIOR DETECTION USING YOLOv8 – 2024"

Advantages - The system is highly effective in crowded environments and significantly reduces false positives, making it reliable for dense crowd monitoring.

Disadvantages - The framework is computationally intensive, requiring powerful hardware for real-time processing and analysis.

[4] **Jyothsna V., Alle C., Kurnutala R., Ganesh K. N., KushalKarthik K. R., and Pydala B.** proposed a concept in which a YOLOv8-based security system was developed to detect individuals, monitor distances, and identify weapons or violent actions in real time. The system enhances security by providing speech alerts and email notifications to security personnel. By integrating multi-modal data, it improves detection accuracy and response efficiency.

"YOLOv8-BASED PERSON DETECTION, DISTANCE MONITORING, SPEECH ALERTS, AND WEAPON IDENTIFICATION WITH EMAIL NOTIFICATIONS – 2024"

Advantages - The system offers a robust, multi-layered security solution with real-time alerts and notifications, improving situational awareness and response time.

Disadvantages - The complexity of system integration requires significant resources for implementation and ongoing maintenance.

[5] **P., Patil S., and Pattanshetti T.** proposed a concept in which a real-time violence and weapon detection system was developed using advanced deep learning techniques. The system analyzes video footage from CCTV cameras to identify violent actions or weapons and triggers immediate alerts to security personnel. This approach enhances public safety by ensuring rapid response to potential threats.

"REAL-TIME VIOLENCE AND WEAPON DETECTION AND ALERT SYSTEM – 2024"

Advantages - The system achieves high accuracy in detecting threats and significantly reduces response time to incidents, improving public security.

Disadvantages - It may produce false positives in densely populated areas and could miss threats in low-quality video footage.

[6] **Kumar R., Rajpurohit D. S., Hanief M., Sharma S., Choudhury T., and Sar A.** proposed a concept in which a system was developed to detect criminal activities by analyzing live CCTV footage. The system leverages machine learning algorithms to identify specific criminal activities such as theft, assault, or vandalism and instantly notifies authorities for prompt intervention.

"DETECTION OF CRIMINAL ACTIVITIES/CRIMINAL THROUGH CCTV BY LIVE FOOTAGE ANALYSIS – 2024"

Advantages - The system enables early identification of criminal activities, significantly reducing response time and improving security measures.

Disadvantages - Its accuracy depends on the quality of CCTV footage and environmental conditions, which may affect detection efficiency.

[7] **Bensakhria A.** proposed a concept in which real-time edge AI video analytics was utilized for threat detection in sensitive environments such as airports, government buildings, and military sites. By processing video data at the edge, the system minimizes latency and enhances real-time decision-making, ensuring quicker responses to potential threats.

"LEVERAGING REAL-TIME EDGE AI-VIDEO ANALYTICS TO DETECT AND PREVENT THREATS IN SENSITIVE ENVIRONMENTS – 2023"

Advantages - The system enables real-time processing at the edge, reducing response time and improving overall security efficiency.

Disadvantages - The implementation requires high computational resources and comes with significant costs for deploying and maintaining edge devices.

[8] **Benoit P., Bresson M., Xing Y., Guo W., and Tsourdos A.** proposed a concept in which a real-time vision-based system was developed to detect violent actions through CCTV cameras using pose estimation. By analyzing human body movements, the system identifies aggression or violent behaviors in public spaces, enhancing public safety through automated surveillance.

"REAL-TIME VISION-BASED VIOLENT ACTIONS DETECTION THROUGH CCTV CAMERAS WITH POSE ESTIMATION – 2023"

Advantages - The system provides high precision in detecting violent actions by analyzing body pose and movement patterns.

Disadvantages - It may struggle with detecting actions when bodies are occluded or in low-light conditions, affecting accuracy.

[9] Reddy K. and Reddy S. proposed a concept in which a smart monitoring system, OccupEye, was developed to track building traffic and animal movement using AI-based video analysis. The system identifies patterns in both human and animal movements, making it useful for wildlife monitoring and efficient building occupancy management.

"OCCUPEYE – BUILDING TRAFFIC AND ANIMAL MONITORING SYSTEM – 2024"

Advantages - The system is versatile, serving dual purposes in wildlife tracking and building management, enhancing efficiency in both domains.

Disadvantages - Implementing the system in complex environments with varied operational conditions may pose challenges to accuracy and reliability. **Sapkota R., Qureshi R., Calero M. F., Badjugar C., Nepal U., Poulose A., and Karkee M.** proposed a comprehensive review detailing the evolution of the YOLO object detection algorithm from its inception to the latest YOLOv10 version. The study highlights advancements in accuracy, speed, and diverse applications in real-time object detection tasks, providing a thorough analysis of the algorithm's development.

"YOLOv10 TO ITS GENESIS: A DECADAL AND COMPREHENSIVE REVIEW OF THE YOU ONLY LOOK ONCE (YOLO) SERIES – 2024"

Advantages - Offers an in-depth understanding of the YOLO algorithm, its improvements, and its capabilities across different versions.

Disadvantages - The review focuses on theoretical advancements and is not directly applicable to specific real-world problems without further adaptation.

[10] **Qaraqe M., Yang Y. D., Varghese E. B., Basaran E., and Elzein A.** proposed a concept in which the Swin Transformer was leveraged to analyze crowd size and detect violent behaviors in real-time. The system processes video data to assess both the density and potential threat level of a crowd, improving situational awareness and security management.

"CROWD BEHAVIOR DETECTION: LEVERAGING VIDEO SWIN TRANSFORMER FOR CROWD SIZE AND VIOLENCE LEVEL ANALYSIS – 2024"

Advantages - The use of the Swin Transformer enhances performance in both crowd detection and violence level analysis, ensuring higher accuracy in real-world scenarios.

Disadvantages - The system demands significant computational resources for real-time processing, making deployment challenging in resource-constrained environments.

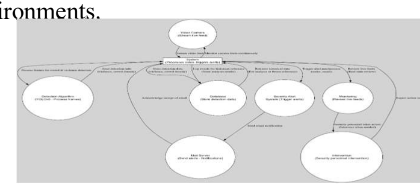


Fig no 1: Data Flow Diagram

III. EXISTING SYSTEM:

Traditional surveillance systems rely on human monitoring, whiere security personnel manually observe live or recorded video feeds to detect suspicious activities. While this method has been in use for decades, it suffers from sevel limitaions, such as human fatigue, observational biases, and delayed response times. As a result, security breaches and violent incidents often go unnoticed until it is too late to intervence effectively. Many security systems use basic motion detection algorithms that analyze pixel changes in consecutive frames. However, these methods are highly prone to false alarms, especially in crowded places where natural movements of people can trigger alerts. Additionally, they lack the ability to differentiate between normal crowd behavior and violent activities, making them unreliable for public safety monitoring. Another major drawback of conventional surveillance systems is their lack of real-time responsiveness. Most security footage is reviewed after an incident has occurred, which limits the ability to prevent crimes or respond quickly to violent situations. This results in significant delays in law enforcement actions, increasing the risk to public safety. Finally, lack of integration with alert mechanisms in current systems reduces their effectiveness. Even if an AI model detects a potential threat, many systems do not provide immediate notifications to security personnel. This means that without an operator actively watching the feed, threats may go unnoticed for extended periods, leading to security failures. Traditional surveillance systems face multiple challenges that hinder their effectiveness in ensuring security and rapid incident response.

Manual monitoring ineffeciencies: Surveillance often requires continuous human oversight, relying on security personnel to manually analyze footage for potential threats. This approach is costly, labor-intensive, and highly prone to fatigue, which can compromise vigilance and response times. Inconsistencies in threat assessment due to human interpretation further increase the risk of critical incidents being overlooked. Limited Real-Time Processing: While some systems integrate motion detection and behavioral analysis, they struggle with real-time data processing. The high volume and velocity of video streams often overwhelm these systems, leading to significant delays between incident occurrence and detection. Such delays can be critical in emergency situations where rapid intervention is essential. Inaccuracy and False Alarms: Many conventional surveillance systems rely on outdated algorithms that fail to distinguish normal activities from genuine threats accurately. This results in frequent false positives—triggering unnecessary alarms—and false negatives—failing to detect actual dangers. Over time, these inaccuracies erode trust in the system, desensitize operators, and create inefficiencies in security management. Lack of Integrated Responses: Most traditional surveillance systems operate in isolation, capable of generating alerts but lacking automated integration with emergency response mechanisms. This means security teams must manually verify and escalate incidents, delaying response times and increasing the potential for lapses in crisis management.

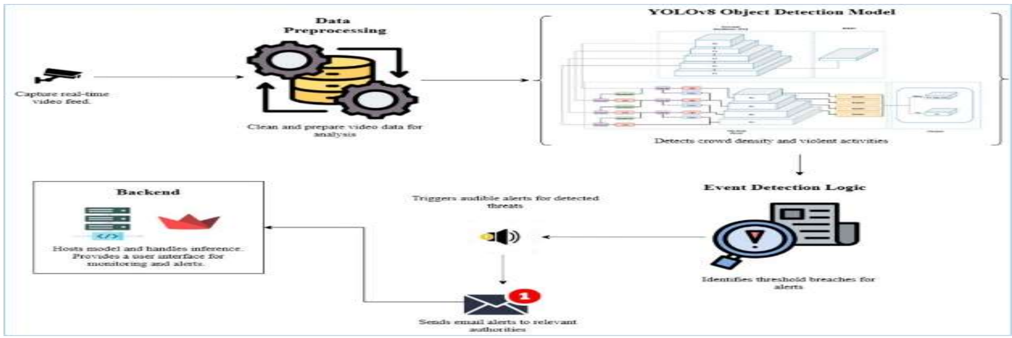


Fig no 2: Architecture Diagram

IV. PROPOSED SYSTEM

The proposed surveillance system integrates the advanced capabilities of YOLOv8, enabling real-time detection of crowd density fluctuations and violent activities to enhance security in public settings. As the latest iteration in the You Only Look Once algorithm series, YOLOv8 leverages cutting-edge deep learning techniques to process high-resolution video feeds in real time, ensuring immediate identification of potential threats and abnormal behaviors. A key advancement of this system is its real-time anomaly and violence detection, powered by deep convolutional neural networks that process and analyze video frames at high speeds without compromising accuracy. Unlike traditional models, YOLOv8 can distinguish subtle nuances in crowd movements and detect abrupt behavioral changes, providing precise alerts almost instantaneously. This capability is crucial in preventing or mitigating security incidents, allowing immediate action before situations escalate. Additionally, the system incorporates an automated alert mechanism that activates audible alarms within the monitored environment and dispatches email notifications to designated authorities or security personnel. This dual-alert feature ensures both onsite and remote teams are informed in real time, facilitating a swift, coordinated response while reducing dependency on constant human oversight. Security staff can focus on strategic intervention rather than continuous monitoring, improving operational efficiency. The benefits of the system are substantial, starting with increased accuracy and reduced false alarms. The advanced deep learning models within YOLOv8 significantly enhance precision, minimizing false positives and negatives, thus improving reliability and conserving security resources. By reducing unnecessary alerts, security personnel can focus on genuine threats, ensuring efficient surveillance protocols. Moreover, the system's rapid detection and alert capabilities play a vital role in enhancing public safety by enabling quick responses to potential dangers, preventing escalations, and effectively managing public spaces. The system can be tailored to specific requirements, including adjustments in camera configurations and processing power, ensuring optimal performance across different operational scales. This flexibility makes it a versatile solution for diverse security needs, reinforcing its effectiveness in dynamic public environments. By leveraging the power of YOLOv8, the proposed system revolutionizes security surveillance with real-time detection, automated alerts, an intuitive interface, continuous improvement, and unparalleled scalability, collectively strengthening public safety measures with cutting-edge technology.

V. METHODOLOGY

a) YOLO Object Detection Model

You Only Look Once (YOLO) is a deep learning-based object detection algorithm optimized for real-time applications. Unlike traditional methods like R-CNN, which scan images multiple times, YOLO processes the entire image in a single pass, significantly improving detection speed. The algorithm employs a grid-based approach,dividing the image into multiple cells. Each cell predicts bounding boxes, class probabilities, and confidence scores simultaneously. This enables the model to detect multiple objects in a single frame, reducing computational complexity. YOLOv8 introduces several enhancements for higher precision and recall, making it more efficient for tasks such as violence detection and crowd monitoring. Improvements include: Better feature extraction for detecting smaller objects, Optimized anchor box assignments for more accurate bounding box predictions and Enhanced neural network layers for faster and more efficient processing.

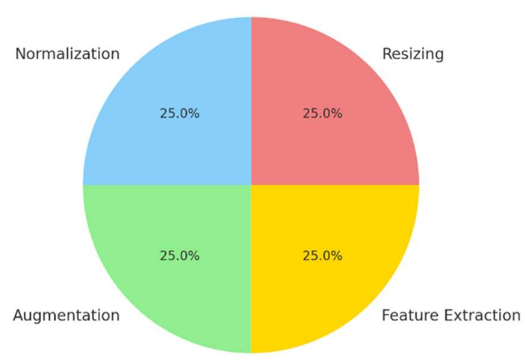


Fig no 3: Data Preprocessing Steps for Image Processing

b) Data Preprocessing in Deep Learning

Data preprocessing is a crucial step in training deep learning models, as raw data often contains noise, inconsistencies, and irrelevant information. Preprocessing ensures that the data is clean, structured, and optimized for better learning performance.For image-based models like YOLOv8, preprocessing involves image resizing, normalization, augmentation, and feature extraction. These steps help in improving model generalization and accuracy.

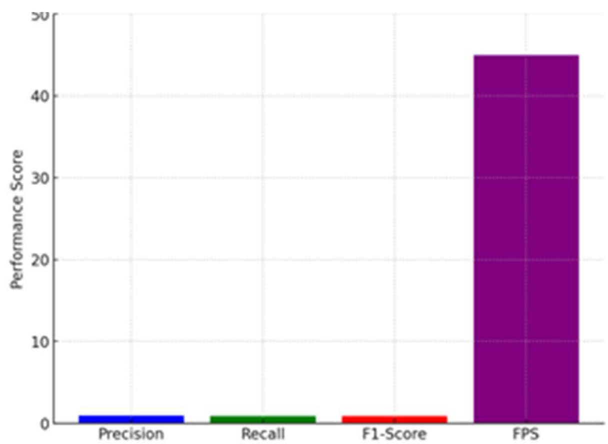


Fig no 4: YoloV8 Object Detection Performance Metrics

c) Data Augmentation Techniques

Data augmentation involves artificially expanding the training dataset by applying transformations such as rotation, flipping, brightness adjustments, and noise addition. This helps the model learn robust features, improving its performance on real-world data. For this project, images in the dataset are augmented with different lighting conditions, angles, and resolutions, allowing the model to detect violent activities in various environments.

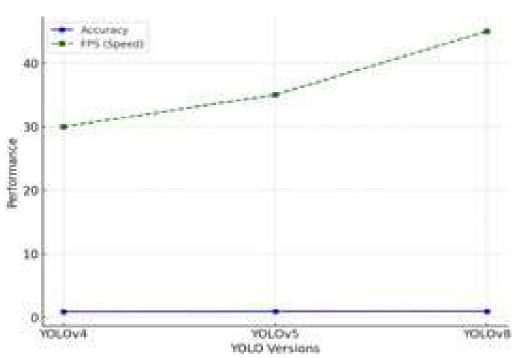
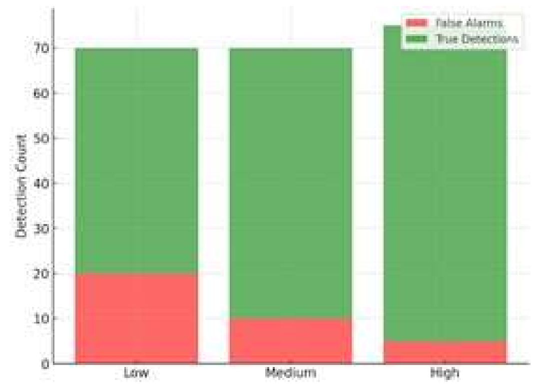


Fig no 5: Comparison of YOLO Versions in Terms of Accuracy and Speed

d) Feature Extraction and Object Localization

Feature extraction involves identifying key patterns in an image, such as edges, textures, and object contours. Deep learning models use convolutional layers to extract these features automatically.For violence detection, features such as body posture, hand movements, and crowd density patterns are extracted. These features help differentiate normal behaviors from aggressive actions, improving detection accuracy.

Fig no 6: Alert System Activation Rate based on Detection Thresholds



VI. DATABASE DESIGN

The database for the real-time crowd and violence detection system is designed for high-throughput and rapid data retrieval to efficiently handle video streams and analytics. It consists of several key tables: The Videos Table stores metadata about video feeds, including VideoID, CameraID, StartTime, EndTime, and StoragePath, enabling efficient indexing and retrieval. The Detections Table logs each event detected by the YOLOv8 algorithm, with fields like DetectionID, VideoID (foreign key), Timestamp, Type (e.g., crowd increase, violent act), and ConfidenceScore, supporting real-time alerts and historical analysis. The Alerts Table tracks issued alerts, containing AlertID, DetectionID(foreign key), SentTime, and ResponseStatus, ensuring accountability. The Users Table manages system operators with fields such as UserID, Username, PasswordHash, Email, and Role (e.g., administrator, viewer), supporting access control. Lastly, the Logs Table records system operations and user activities, storing LogID, UserID (foreign key), ActivityType, Description, and Timestamp, aiding troubleshooting and monitoring.

VII. CONCLUSION AND FUTURE WORK

Future enhancements will focus on integrating audio-based violence detection to identify gunshots, screams, and distress signals, improving accuracy through multimodal analysis. Additionally, edge computing and IoT-enabled real-time processing will allow deployment on low-power devices, making the system more scalable for smart city surveillance networks. Further improvements in predictive analytics, AI-driven behavioral analysis, and multi-camera synchronization will enhance threat anticipation and coordinated security responses.

Cloud-based deployment on platforms like AWS and Google Cloud will enable remote access for law enforcement agencies, ensuring faster decision-making and incident response. These advancements will make the system more flexible and accessible across different security infrastructures, allowing seamless integration with existing surveillance frameworks. With improved AI models, real-time processing, and cloud support, the system aims to enhance both security efficiency and incident management.

The real-time crowd and violence detection system using YOLOv8 represents a major advancement in AI-powered surveillance, offering automated real-time detection and alert mechanisms to enhance public safety and security operations. By leveraging deep learning and computer vision, the system efficiently identifies sudden crowd density changes and violent activities, ensuring rapid response by security personnel. The integration of real-time notifications, sound alarms, and an interactive monitoring dashboard minimizes the reliance on manual surveillance, reducing response time and improving situational awareness. With high accuracy and processing speed, the system is adaptable for deployment in high-risk areas such as public events, transportation hubs, and commercial spaces. However, challenges such as false positives in densely populated areas, sensitivity to varying lighting conditions, and computational resource requirements highlight the need for further optimization.

VIII. REFERENCE

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