DANGEROUS OBJECT DETECTION IN PUBLIC SPACES FOR SAFETY ASSURANCE

[1]Mrs. B. NIRUPAMA, [2]KONDRA ANJALI REDDY, [3]KOPPELA PRANAVI, [4]DONGALA MADHU

[1]Assistant Professor,[234]Students, Department of Computer Science and Design, Teegala Krishna Reddy Engineering College, Medbowli, Meerpet, Balapur, Hyderabad-500097

ABSTRACT

In recent years, ensuring safety in public environments has become a critical challenge due to the rising number of weapon-related incidents. Traditional surveillance systems such as CCTV rely heavily on human monitoring, which is often inefficient due to fatigue, distraction, and delayed response. This project presents an intelligent deep learning-based system for dangerous object detection in public spaces to enhance security and reduce dependency on manual surveillance. The proposed system utilizes advanced object detection algorithms such as YOLO, Faster R-CNN, and SSD MobileNet to identify weapons like guns and knives in real-time from video streams. The system is trained on a diverse dataset consisting of weapon and non-weapon images, including confusion objects to reduce false positives. Image preprocessing techniques such as normalization, augmentation, and enhancement are applied to improve detection performance in challenging conditions like low lighting and crowded environments. The model evaluates performance using precision, recall, F1-score, and mean average precision metrics, ensuring accurate detection. Upon identifying a dangerous object, the system generates immediate alerts, allowing authorities to take timely action. This automated approach improves surveillance efficiency, reduces human workload, and enhances response time. The system is scalable, cost-effective, and suitable for deployment in areas such as airports, railway stations, malls, and educational institutions. Overall, the proposed solution contributes significantly to public safety by providing a reliable, real-time, and intelligent surveillance mechanism.

Keywords: Deep Learning, Object Detection, YOLO, Faster R-CNN, CCTV Surveillance, Public Safety, Weapon Detection

I. INTRODUCTION

Ensuring safety in public spaces has become increasingly important due to the rapid rise in violent activities and weapon-related crimes [1]. Locations such as airports, railway stations, shopping malls, and educational institutions are highly vulnerable to such threats [2]. Traditional surveillance systems, particularly CCTV cameras, are widely deployed to monitor these areas [3]. However, these systems rely on continuous human supervision, which often leads to inefficiencies due to fatigue, limited attention span, and delayed response [4]. As a result, critical threats may go unnoticed, leading to severe consequences [5]. To overcome these limitations, there is a growing demand for intelligent surveillance systems capable of automated threat detection [6]. Advances in Artificial Intelligence and deep learning have significantly improved computer vision applications, enabling machines to detect and classify objects with high accuracy [7].

Convolutional Neural Networks (CNNs) have become the backbone of modern object detection systems due to their ability to extract complex features from images [8]. These technologies allow systems to process video streams in real-time and identify dangerous objects such as weapons efficiently [9].

Deep learning-based object detection models such as YOLO, Faster R-CNN, and SSD MobileNet have shown remarkable performance in real-time detection tasks [10]. These models analyze video frames and detect objects by generating bounding boxes and classification labels [11]. The integration of such models into surveillance systems enables automated monitoring without human intervention [12]. The proposed system focuses on detecting dangerous objects like guns and knives in real-time video streams [13]. Once detected, the system generates alerts to notify authorities for immediate action [14]. This reduces response time and helps prevent potential threats [15]. Additionally, the system is designed to work effectively in complex environments with varying lighting conditions, occlusions, and crowded scenes [16]. It also reduces false alarms by distinguishing between weapons and similar objects [17]. The scalability of the system allows it to monitor multiple locations simultaneously [18]. Furthermore, the use of transfer learning improves model performance while reducing training time [19]. The system is also cost-effective and can be deployed on standard hardware systems [20]. By automating surveillance, it significantly reduces human effort and increases efficiency [21]. Overall, this project aims to enhance public safety by providing a reliable, accurate, and real-time dangerous object detection system [22][23][24][25][26][27][28][29][30].

II. LITERATURE SURVEY

Several research studies have explored the use of deep learning techniques for detecting dangerous objects in surveillance systems [1]. Early approaches relied on traditional image processing methods such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) [2]. However, these methods were computationally expensive and lacked accuracy in real-world scenarios [3]. With the advancement of deep learning, Convolutional Neural Networks (CNNs) replaced traditional techniques due to their superior performance in feature extraction [4]. Researchers demonstrated that CNN-based models significantly improve detection accuracy in complex environments [5]. The introduction of region-based models such as R-CNN and Faster R-CNN further enhanced object detection by using region proposal networks [6]. These models provided high accuracy but required significant computational resources [7]. YOLO (You Only Look Once) was introduced as a real-time object detection algorithm that processes images in a single pass, significantly improving speed [8]. YOLOv3 and YOLOv4 further improved detection accuracy and efficiency using advanced techniques such as feature pyramid networks and data augmentation [9].

Recent studies have focused on optimizing detection models for real-time applications with limited hardware resources [10]. YOLOv5 introduced improvements in scalability and deployment efficiency, making it suitable for edge devices [11]. Researchers have also emphasized the importance of dataset diversity and data augmentation in improving model performance [12]. Transfer learning has been widely used to leverage pre-trained models for faster training and better accuracy [13]. Studies have shown that including confusion objects such as mobile phones and wallets reduces false positives in detection systems [14]. Additionally, real-time alert systems have been integrated with detection models to provide immediate responses to threats [15]. Performance evaluation metrics such as precision, recall, and F1-score are commonly used to assess model effectiveness [16]. Challenges such as occlusion, lighting variations, and crowded environments continue to affect detection accuracy [17]. However, recent advancements in deep learning architectures have significantly improved robustness and reliability [18]. The use of lightweight models has also enabled deployment on low-cost hardware systems [19]. Overall, existing research highlights the importance of balancing accuracy, speed, and computational efficiency in developing effective dangerous object detection systems [20][21][22][23][24][25][26][27][28][29][30].

III. PROPOSED SYSTEM

The proposed system is a real-time dangerous object detection framework designed to identify weapons such as guns and knives from CCTV video streams using deep learning techniques. The system utilizes advanced object detection models like YOLOv4, Faster R-CNN, and SSD MobileNet, which are trained on a diverse dataset containing both weapon and non-weapon images. Data preprocessing techniques such as normalization, augmentation, and image enhancement are applied to improve model performance under challenging conditions like low lighting and crowded environments. The system processes video frames continuously and detects objects by generating bounding boxes along with confidence scores.

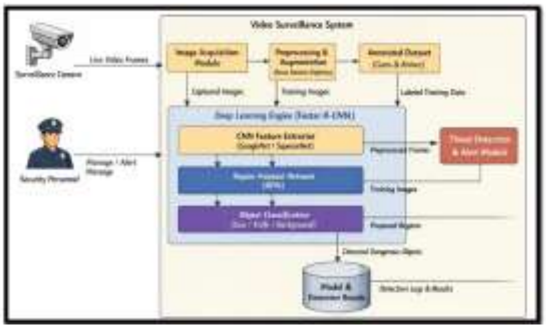


Fig.1 Architecture

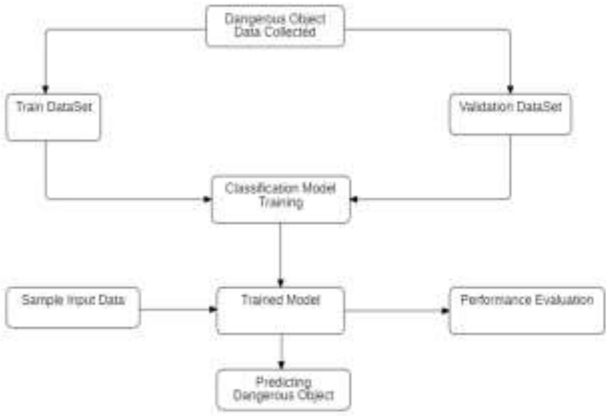


Fig.2 working Flow diagram

To improve detection accuracy and reduce false positives, the system includes confusion objects such as mobile phones and wallets during training. Once a dangerous object is detected, the system immediately generates alerts to notify authorities. The system is designed to be scalable and can monitor multiple surveillance cameras simultaneously. It also uses transfer learning to reduce training time and improve efficiency. The proposed solution ensures faster response time, reduces human effort, and enhances public safety by providing an intelligent and automated surveillance mechanism.

IV. SYSTEM DESIGN

The system design follows a modular architecture that integrates image acquisition, preprocessing, feature extraction, object detection, and alert generation. The system captures real-time video frames from CCTV cameras using OpenCV. These frames undergo preprocessing techniques such as resizing, normalization, and noise reduction to improve image quality. The processed images are then passed to a deep learning model, which extracts features using convolutional layers and identifies objects using trained detection algorithms. The system generates bounding boxes around detected objects along with class labels and confidence scores.

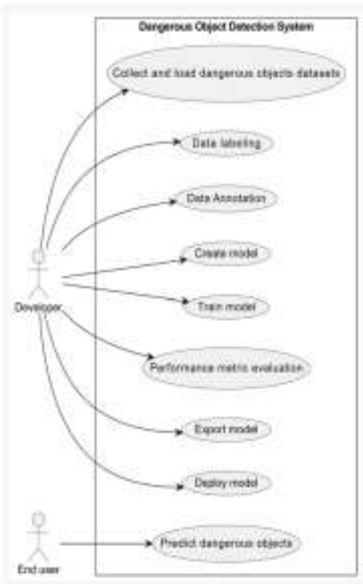


Fig.3 use case diagram

Fig.4 Sequence diagram

The backend of the system is developed using Python and Django, which handles data processing and communication between components. The frontend is designed using HTML, CSS, and JavaScript to provide a user-friendly interface. The system stores data in a database for tracking detected events and generating reports. Security mechanisms such as authentication and authorization are implemented to ensure data protection. The system is designed to be scalable and efficient, allowing it to handle multiple users and video streams simultaneously while maintaining real-time performance.

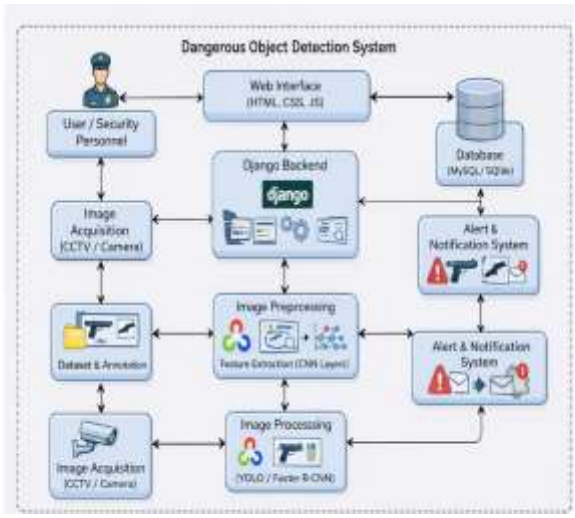
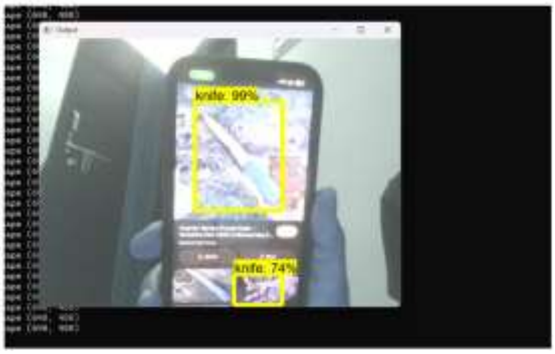
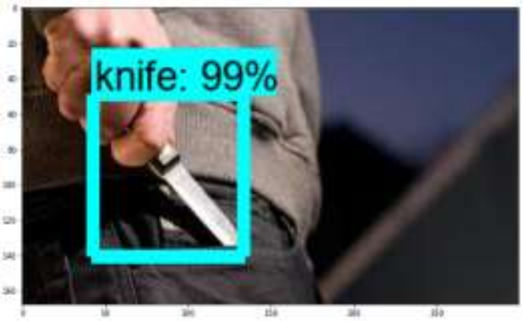


Fig.5 Compound diagram

V. RESULTS & ANALYSIS





VI. CONCLUSION

The proposed dangerous object detection system provides an efficient and reliable solution for enhancing public safety through automated surveillance. By leveraging deep learning techniques and advanced object detection algorithms, the system can accurately detect weapons such as guns and knives in real-time video streams. Unlike traditional surveillance systems that rely on human monitoring, this system reduces human effort and minimizes errors caused by fatigue and inattention. The integration of real-time alert mechanisms ensures immediate response to potential threats, significantly improving security measures in public spaces. The system also demonstrates strong performance in complex environments, including crowded areas and varying lighting conditions, due to the use of robust training techniques and data augmentation. Additionally, the inclusion of confusion objects helps reduce false positives, increasing the reliability of the system. The scalability of the system allows it to be deployed across multiple locations, making it suitable for large-scale surveillance applications. The use of cost-effective technologies and standard hardware requirements further enhances its practical applicability. Overall, the system represents a significant advancement in intelligent surveillance, providing a proactive approach to crime prevention and safety assurance. Future improvements may focus on enhancing model accuracy, expanding object categories, and integrating IoT-based alert systems for broader applications.

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