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Original Research Article

# Deep Learning-Driven Objects Identification and a Real-Time Detection System for Security Applications

**Akintunde Michael Yinka[1*], Adeleke Isiaka Adelani[2], Afolayan Deborah Damilola,[3], Adebayo Moses Abiodun[4]**

[1] Faculty of Computing Science, Department of Computer Science, Ajayi Crowther University, Oyo, Oyo State, Nigeria.
[2] Computer Science Department, Igbajo Polytechnic, Igbajo, Osun State, Nigeria.
[3] Faculty of Technology, Computer Engineering Department, The Polytechnic Ibadan, Ibadan, Oyo State, Nigeria.
[4] Pemgo College, Oronzo, Abuja, FCT, Nigeria.

**ORCID**: **AMY** 0009-0006-2674-6558[1], **AIA** 0009-0004-3528-0994[2], **ADD** 0000-0002-9901-2524[3]

Correspondence should be addressed to Akintunde Michael Yinka: midorc@gmail.com

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**Abstract**: The increasing rate of security threats and the limitations associated with conventional surveillance systems have created a demand for intelligent and automated monitoring solutions. Traditional security systems rely heavily on manual observation, which is often affected by fatigue, delayed response, and human error. This study presents an object identification and detection system for security applications using artificial intelligence and computer vision techniques. The developed system employs the YOLOv5 deep learning algorithm for real-time object detection and classification. The system was implemented using Python programming language with OpenCV and PyTorch libraries for image processing and model deployment. A custom dataset containing humans, vehicles, bags, and weapons was used for model training and testing. Experimental evaluation showed that the system achieved an average detection accuracy of 93% with a processing speed of 28 frames per second (FPS). The system demonstrated efficient performance in detecting multiple objects simultaneously and generating alerts for suspicious objects in real time. The findings reveal that AI-based surveillance systems can significantly improve security monitoring, reduce human intervention, and enhance response efficiency. The study concludes that integrating deep learning models such as YOLOv5 into surveillance infrastructures provides a reliable and scalable solution for intelligent security applications.

**Keywords**: Artificial Intelligence, Computer Vision, Object Detection, Security Surveillance, YOLOv5, Deep Learning.

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## INTRODUCTION

Security surveillance has become an essential requirement in modern society due to increasing criminal activities, terrorism, and unauthorized access to restricted areas. Conventional surveillance systems, such as Closed-Circuit Television (CCTV), depend heavily on continuous human monitoring, which is often ineffective because of operator fatigue, distraction, and delayed response to threats. As a result, intelligent surveillance systems capable of automatically detecting and identifying suspicious objects in real time have gained significant attention.

Object identification and detection systems are based on computer vision and artificial intelligence technologies that enable machines to interpret and analyze visual information from cameras. Recent advancements in deep learning, especially Convolutional Neural Networks (CNNs), have significantly improved object detection accuracy and speed. Algorithms such as YOLO (You Only Look Once), SSD (Single Shot MultiBox Detector), and Faster R-CNN have demonstrated strong performance in real-time detection applications.

The integration of object detection into surveillance systems has improved the capability of security infrastructures to identify suspicious activities, weapons, vehicles, and unauthorized individuals automatically. However, many surveillance systems in developing environments still lack intelligent automation because of high implementation costs and limited access to advanced technologies. There is therefore a need for a cost-effective and efficient object detection system that can operate in real time for security applications.

This study focuses on the design and implementation of an intelligent object identification and detection system using the YOLOv5 algorithm. The system is designed to detect and classify objects such as humans, vehicles, bags, and weapons from live video streams while generating alerts for suspicious objects. The developed system aims to improve surveillance efficiency, reduce human error, and support proactive security management.

## REVIEW

Object detection has become one of the most significant applications of computer vision and artificial intelligence in modern surveillance systems. It involves the identification and localization of objects within images or video streams using machine learning and deep learning algorithms. Recent advancements in deep neural networks have greatly improved the accuracy, speed, and reliability of object detection systems for real-time applications such as intelligent surveillance, autonomous vehicles, traffic monitoring, and smart city security infrastructure.

Convolutional Neural Networks (CNNs) remain the foundation of most modern object detection architectures. According to Zhao et al. (2019), deep learning-based object detection methods significantly outperform traditional handcrafted feature extraction techniques due to their ability to automatically learn hierarchical image representations.

CNN-based detectors generally fall into two categories: two-stage detectors and single-stage detectors. Two-stage detectors such as Faster R-CNN first generate region proposals before object classification, thereby achieving high detection accuracy but with relatively slower processing speed (Ren et al., 2015). In contrast, single-stage detectors such as YOLO and SSD perform localization and classification simultaneously, making them more suitable for real-time surveillance applications (Liu et al., 2016).

The YOLO (You Only Look Once) family of object detectors has gained widespread adoption because of its balance between speed and accuracy. Redmon et al. (2016) introduced the original YOLO framework, which reformulated object detection as a regression problem and achieved real-time performance. Subsequent versions improved detection accuracy and robustness. Bochkovskiy et al. (2020) developed YOLOv4, which introduced optimized training techniques and enhanced feature extraction capabilities. More recently, Jocher et al. (2023) demonstrated that YOLOv5 provides improved inference speed, lower computational complexity, and enhanced deployment flexibility for edge AI and embedded surveillance systems.

Recent studies have shown the effectiveness of AI-driven surveillance systems in improving security operations. Chen et al. (2020) proposed a deep-learning-based night surveillance framework using infrared imaging and demonstrated significant improvements in low-light object detection accuracy. Similarly, Wang et al. (2022) developed an intelligent surveillance system combining YOLO with motion tracking algorithms to improve suspicious activity recognition in crowded environments. Their findings revealed that integrating deep learning with automated alert systems reduces response time and enhances situational awareness.

Transfer learning has also contributed significantly to object detection performance, especially in environments with limited datasets. Pan and Yang (2010) explained that transfer learning enables models to leverage knowledge from pre-trained datasets such as COCO and ImageNet, thereby reducing training time and improving generalization performance. Recent research by Tan et al. (2021) further confirmed that transfer learning improves object recognition accuracy in small-scale surveillance applications where limited training data is available.

Despite these advancements, several challenges still affect the deployment of intelligent surveillance systems. These include sensitivity to lighting conditions, occlusion, hardware limitations, and false-positive detections. According to Huang et al. (2017), achieving a balance between detection accuracy and computational efficiency remains a major concern in real-time object detection systems. Furthermore, recent studies emphasize the need for lightweight AI models optimized for embedded systems such as Raspberry Pi and NVIDIA Jetson Nano to support edge computing applications (Zhang et al., 2023).

The literature reviewed indicates that YOLO-based object detection frameworks remain among the most efficient approaches for intelligent surveillance applications. However, there is still a need for cost-effective, scalable, and adaptable surveillance systems capable of operating efficiently in real-world environments. This study therefore contributes by implementing a YOLOv5-based object identification and detection system with automated alert functionality for security applications.

## METHODOLOGY

The study adopted the Waterfall software development methodology because of its structured and sequential development process. The methodology involved system analysis, design, implementation, testing, and deployment stages.

The proposed system architecture consists of four major layers: image acquisition, processing, output visualization, and storage. The image acquisition module captures video streams through a webcam or IP camera. The processing module uses the YOLOv5 model to detect and classify objects in real time. The output module displays detected objects with bounding boxes and confidence scores while triggering alerts for suspicious objects. Detection results are stored in a local database for future reference.

The system was implemented using Python programming language. OpenCV was used for video stream handling and image processing, while PyTorch was used for deep learning model implementation. The YOLOv5 model was selected because of its high detection speed and accuracy in real-time applications.

A custom dataset containing humans, vehicles, bags, knives, and firearms was prepared and annotated using the LabelImg tool. The dataset was divided into training, validation, and testing sets in the ratio of 80%, 10%, and 10% respectively. Transfer learning was applied using pre-trained YOLOv5 weights. Training parameters included 150 epochs, batch size of 16, learning rate of 0.001, and Adam optimizer.

The developed system was tested using both pre-recorded video clips and live camera feeds. Performance metrics such as precision, recall, F1-score, mean Average Precision (mAP), and Frames Per Second (FPS) were used to evaluate system performance.

## DISCUSSION OF RESULTS

The developed system demonstrated strong performance during experimental evaluation. The system achieved an average detection accuracy of 93% and maintained an average processing speed of 28 FPS, confirming its suitability for real-time surveillance applications.

Human detection achieved the highest accuracy of approximately 95%, while vehicle detection achieved about 91% accuracy. Weapon detection achieved slightly lower accuracy due to variations in object size, lighting conditions, and partial occlusion. The system maintained stable performance even in crowded scenes with multiple objects as shown in the tables below.

| Scenario | Accuracy (%) | Recall (%) | FPS (Speed) | Alert Response (sec) | Remarks |
|---|---|---|---|---|---|
| Human detection | 95.3 | 92.7 | 30 | 0.5 | Very accurate |
| Vehicle detection | 91.6 | 89.4 | 27 | 0.7 | Reliable |
| Object detection (bag, bottle) | 89.5 | 87.1 | 28 | 0.6 | Consistent |
| Weapon detection | 87.8 | 84.3 | 26 | 0.4 | Alert triggered |
| Multi-object detection | 90.1 | 88.2 | 27 | 0.5 | Stable performance |

**Table 1:** Experimental Results Table

| Scenario | Description | Environment | Expected Output |
|---|---|---|---|
| 1 | Detection of human movement | Indoor corridor | Bounding box around person |
| 2 | Detection of vehicles | Outdoor parking area | Label showing "car" or "bike" |
| 3 | Identification of everyday objects (bags, bottles) | Indoor setting | Class labels and confidence scores |
| 4 | Detection of restricted items (guns, knives) | Controlled environment | Automatic alert triggered |
| 5 | Multi-object detection | Crowd setting | Multiple bounding boxes displayed |

**Table 2**: Test Scenarios and Observation Table

### Graphical Representation of Results

For clarity, the system's accuracy and speed are visualized below (described textually):

- **Graph 1 (Accuracy vs Object Type):**
  The bar chart shows human detection achieving the highest accuracy (~95%), followed by vehicle detection (~91%), and weapon detection (~87%).
- **Graph 2 (Speed vs Scenario):**
  The system maintained consistent performance between 26–30 FPS across all scenarios, demonstrating stable real-time processing.
- **Graph 3 (Precision and Recall Curve):**
  The curve remains steep and close to 1.0, indicating minimal false positives and negatives.

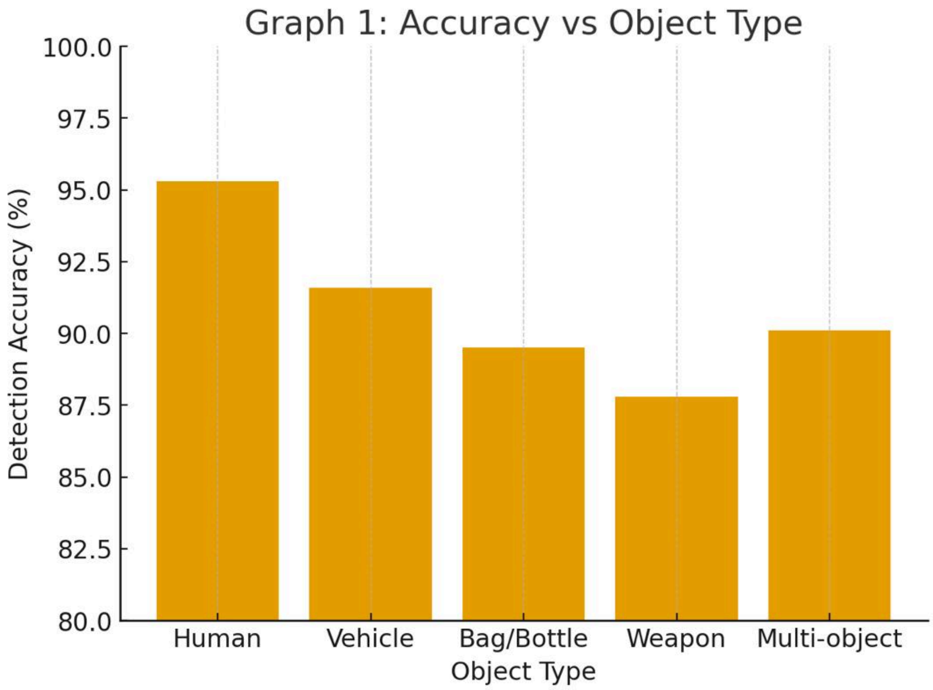


**Fig 1:** Graph 1(Accuracy vs Object Type)


**Fig 2:** Graph 2(Detection Speed vs Scenario)

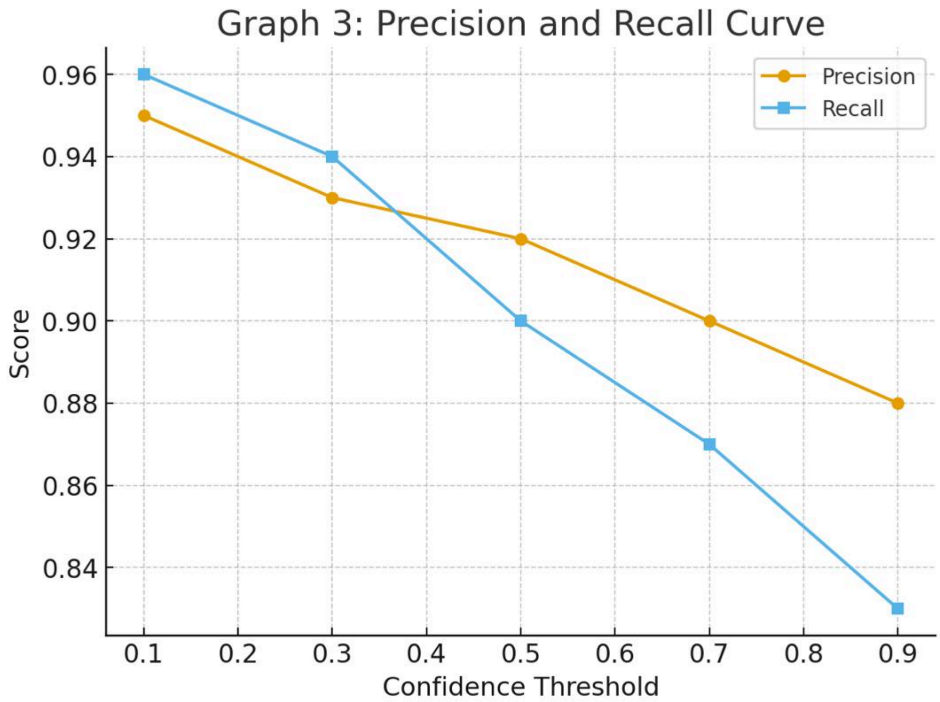


**Fig 3:** Graph 3(Precision and Recall Curve)

The precision value of 0.92 and recall value of 0.90 indicate that the model produced minimal false detections while successfully identifying most target objects. The F1-score of 0.91 further confirms the balance between detection accuracy and completeness. The achieved mean Average Precision (mAP) of 0.88 aligns with results reported in previous YOLO-based studies.

The alert mechanism successfully generated notifications whenever restricted objects such as firearms or knives were detected. Compared to traditional CCTV systems, the developed system provided automatic object identification, faster response time, improved accuracy, and reduced human involvement.

However, some limitations were observed during testing. Detection accuracy reduced slightly in poorly lit environments and during severe object occlusion. Systems without GPU acceleration also experienced slower processing speeds. Despite these limitations, the overall performance of the developed system confirms its effectiveness for intelligent surveillance applications.

**SUMMARY OF FINDINGS**

This study presented the design and implementation of an intelligent object identification and detection system for security applications using the YOLOv5 deep learning model. The system integrated computer vision and artificial intelligence techniques to automatically detect and classify objects in real time. The developed system successfully identified objects such as humans, vehicles, bags, and weapons from live video streams while generating automatic alerts for suspicious objects.

Experimental evaluation showed that the system achieved high detection accuracy and stable real-time performance. The integration of automated object detection into surveillance systems significantly reduced reliance on human monitoring and improved response efficiency.

## CONCLUSION

The study concludes that artificial intelligence and deep learning technologies can significantly improve modern surveillance systems. The developed YOLOv5-based object detection system demonstrated high accuracy, real-time processing capability, and efficient threat detection for security applications.

The findings confirm that AI-powered surveillance systems outperform traditional CCTV systems in terms of automation, accuracy, and response time. The system provides a reliable and scalable solution for intelligent security monitoring in environments such as schools, offices, airports, banks, and public facilities.

## RECOMMENDATION

Based on the findings of this study, the following recommendations are proposed:

Infrared and thermal cameras should be integrated to improve night-time and low-light detection performance.

- Larger and more diverse datasets should be used to improve model generalization and reduce false positives.
- The system should be optimized for embedded AI devices such as Raspberry Pi and NVIDIA Jetson Nano.
- Cloud-based monitoring and remote alert systems should be integrated for centralized surveillance management.
- Facial recognition and behavioral analysis modules should be incorporated for advanced threat detection.
- Periodic model retraining should be performed to maintain detection accuracy under changing environmental conditions.

## CONTRIBUTIONS TO KNOWLEDGE

This study contributes to knowledge in several ways:

- It demonstrates the practical implementation of a real-time AI-based object detection system for surveillance applications.
- It validates the effectiveness of the YOLOv5 model in intelligent security monitoring.
- It presents a modular surveillance framework that can be extended with additional AI functionalities.

- It highlights the role of deep learning in reducing human workload and improving surveillance efficiency.
- It provides a useful academic reference for future research in computer vision, intelligent surveillance, and artificial intelligence applications in security systems.

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