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Real-Time Weapon Detection and Restricted Zone Intrusion Monitoring Using Deep Learning and Spatial Analysis

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Abstract

Security surveillance systems play a vital role in safeguarding public and private spaces. However, traditional surveillance systems rely heavily on manual monitoring, which is in- efficient and prone to delayed responses. This research presents a real-time surveillance alert system capable of detecting knives in live video streams and identifying intrusions within user-defined restricted zones. The system integrates a YOLO-based deep learning model for weapon detection with polygon-based spatial reasoning for intrusion analysis. The proposed framework facilitates accurate threat identification, real-time alert genera- tion, and visual annotation of security breaches.

Keywords: YOLO; Weapon Detection; Real-Time Surveillance; Intrusion Detection; Computer Vision

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1 Introduction

The growing occurrence of violent incidents across public and private environments has height- ened the need for intelligent surveillance systems capable of real-time threat detection. Conven- tional CCTV systems depend predominantly on human monitoring, making them susceptible to fatigue, oversight, and delayed responses [1].

Over time, automated surveillance systems have progressed from basic motion detection and rule-based techniques to more advanced machine learning driven approaches. Early methods relied solely on handcrafted features and classical classifiers, which often failed under complex conditions [5]. Recent advancements in artificial intelligence, particularly deep learning and computer vision, have significantly transformed automated surveillance systems. Object detec- tion algorithms such as YOLO facilitate high-speed and high-accuracy identification of objects within video streams [4, 8]. When combined with spatial reasoning, these systems extend be- yond basic threat detection to contextual awareness, enabling the identification of violations such as unauthorized access to restricted areas.

Problem Statement: There is a clear need for an intelligent system capable of real-time weapon detection and restricted-area monitoring. Existing approaches often lack contextual awareness, scalability, and the ability to provide timely alerts, limiting their effectiveness and reliability in real-world security scenarios [3].

To address these challenges, this research proposes a real-time weapon detection and restricted- area intrusion monitoring system that integrates deep learning based object detection with ge- ometric analysis. The proposed system is designed to be interactive, scalable, and suitable for real-world security applications.

1.1 Classification of Algorithms for Intelligent Surveillance Systems

In the context of intelligent surveillance and security monitoring, supervised learning, deep learning based object detection, and rule-based spatial analysis form the computational foun- dation for real-time threat detection and intrusion monitoring. Supervised deep learning facil- itates weapon detection and real-time object localization, while rule-based geometric analysis permits the identification of restricted-area intrusions.

1.1.1 Supervised Learning

Supervised learning plays a crucial role in weapon detection by enabling accurate identification of threat objects from labeled visual data in surveillance footage.

Algorithms Used:

- **YOLO (You Only Look Once):** A real-time object detection algorithm used for fast and accurate identification of weapons [4, 8, 10].
- **Convolutional Neural Networks (CNNs):** They form the backbone of deep learning based object detection models [1] by extracting spatial features from individual frames of live video streams.
- **Transfer Learning Models:**Models pre-trained on extensive datasets and subsequently fine-tuned on weapon-specific data to enhance detection accuracy [9] while reducing train- ing time.

1.1.2 Unsupervised Learning

Unsupervised learning techniques support pattern discovery and scene understanding in surveil- lance environments, facilitating detection of abnormal activities [6]. **Algorithms Used:**

- **K-Means Clustering:** Utilized for grouping motion patterns or scene elements to dis- tinguish normal activity from potential anomalies[5, 6] .
- **Gaussian Mixture Models (GMM):** Applied in background subtraction and motion segmentation for dynamic surveillance scenes.
- **Principal Component Analysis (PCA):** Employed for dimensionality reduction to optimize feature representation and computational efficiency.

1.1.3 Rule-Based and Geometric Reasoning

Rule-based and geometric reasoning mechanisms are employed to analyze spatial relationships and enforce contextual constraints within surveillance zones.

Techniques Used:

- **Polygon-Based Spatial Analysis:** Defines user-specified restricted areas and deter- mines intrusion events based on object-boundary intersections [4, 8].
- **Bounding Box Intersection Logic:** Evaluates overlap between detected objects and restricted regions to confirm violations.
- **Deterministic Decision Rules:** Enables real-time intrusion alerts by combining detec- tion confidence with spatial constraints.

2 Literature Review

Weapon detection using computer vision has attracted substantial attention in recent years due to increasing concerns about public safety and security. Early approaches primarily relied on handcrafted features such as edge, texture, and shape descriptors, combined with classical machine learning classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests [5]. While these methods provided initial insights into automated weapon recognition, they were constrained by limited accuracy, poor generalization to diverse environments, and high sensitivity to variations in lighting, viewpoint, and background clutter. With the emergence of deep learning, convolutional neural networks (CNNs) and region- based detectors have have experienced significant improvements in detection accuracy, com- putational efficiency, and real-time applicability [4, 10].

These models automatically learn hierarchical feature representations from raw image data, eliminating the need for handcrafted feature engineering thereby enabling robust performance in complex and dynamic surveillance scenarios.

Overall, the literature indicates a clear progression from classical machine learning methods toward deep learning and attention-based frameworks, with an increasing emphasis on real-time performance, small object detection, and context-aware reasoning for surveillance applications.

Author(s)	Year	Paper Title	Findings	Technology Used / Dataset
A. Sharma et al.	2021	Object Detection in Deep Surveillance	It proposed a deep learning-based surveillance framework addressing challenges such as occlusion, illumi- nation variation, and real-time con- straints.	CNN-based object detectors; surveillance video datasets.
M. Elharrouss et al.	2023	Object Detection in Real- Time Video Surveillance Us- ing Attention-Based Trans- former–YOLOv8 Model	It integrated transformer-based at- tention mechanisms with YOLOv8, achieving improved accuracy and ro- bustness in real-time surveillance.	Transformer–YOLOv8; real- time surveillance datasets.
R. K. Verma et al.	2022	Intelligent Video Surveillance Using YOLO Object Detec- tion	It demonstrated effective real-time object detection for intelligent surveillance with high detection speed and accuracy.	YOLO-based detecto rs; video surveillance datasets.
Y. Wang et al.	2024	Advancements in Small- Object Detection	It reviewed recent techniques ad- dressing scale variation and low-resolution challenges in small-object detection for surveillance.	Advanced deep learning mod- els; small-object datasets.
X. Zhang et al.	2025	TOE-YOLO: Accurate Tiny Object Detection in UAV Im- agery	It introduced TOE-YOLO, a spe- cialized architecture achieving supe- rior accuracy in detecting tiny ob- jects in aerial surveillance imagery.	YOLO-based architectu re; UAV imagery datasets.

Table 1: Summary of Recent Research on Object Detection in Surveillance Systems Numerous studies have

investigated weapon detection in surveillance footage; however, the

majority concentrate solely on object detection without incorporating spatial intrusion logic. This study addresses this gap by integrating knife detection with restricted-area intrusion anal- ysis, enabling context-aware surveillance.

3 Proposed Methodology and Implementation

Table 2 illustrates the YOLO-based object detection pipeline implemented for real-time knife detection in surveillance video streams [1, 4, 8]. The selected live video is divided into frames and preprocessed for analysis. YOLO extracts key visual features and detects weapons (knives, as defined in the dataset) using bounding boxes and confidence scores, following established real-time object detection frameworks [2, 10]. Low-confidence and duplicate detections are filtered through post-processing techniques to enhance detection accuracy and reliability [11].

Component	Stage	Description	Implementation Details
Input Processing	Frame Acquisition	Video frames are extracted from live streams for real-time analy- sis.	Frames are sampled, resized, and nor- malized to meet YOLO input con- straints.
Feature Extrac - tion	Convolutional Backbone	Spatial features such as edges, textures, and object shapes are extracted.	YOLO backbone uses convolutional layers with batch normalization and activation functions.
Object Detection	Weapon Localiza- tion	Detection and localization of knives within video frames.	Detection head outputs bounding boxes, class probabilities, and confi- dence scores.
Post-Processing	Confidence Filter- ing	Low-confidence and duplicate detections are removed.	Non-Maximum Suppression (NMS) and confidence thresholding refine de- tections.
Output Genera - tion	Detection Results	Final detections are forwarded for intrusion analysis and alert generation.	Bounding box coordinates and confi- dence values are passed to the intru- sion module.

Table 2: YOLO-Based Object Detection Pipeline for Knife Detection

The finalized detection outputs are then forwarded to the intrusion analysis module to support spatial reasoning and real-time alert generation.

3.1 Weapon Surveillance and Intrusion Alert Algorithm

Algorithm 1: Restricted Zone Weapon-Based Surveillance Detection

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Input: Live or recorded video stream V; Pre-trained YOLO-based weapon detection model M; Confidence threshold τ; Restricted zone polygon Z **Output:** Annotated frames and real-time intrusion alerts **Initialization:**

Load model M;

Open video stream V; Read initial frame F_0; **Restricted Zone Setup:**

Initialize polygon Z;

User selects ≥ 3 boundary points on F_0;
Construct closed restricted zone Z; **Detection Phase:**

while V *is active* **do**

- Read frame F;
- Overlay polygon Z on F;
- *weaponDetected* ← *false*; *zoneIntrusion* ← *false*;
- Apply M on F to obtain detections D;
- **foreach** $d \in D$ **do**
  - **if** $confidence(d) \geq \tau$ **then**
    - Extract bounding box (x_1, y_1, x_2, y_2);
    - Compute centroid $c = \left(\frac{x1+x2}{2}, \frac{y1+y2}{2}\right)$;
    - *weaponDetected* ← *true*;
    - **if** $c \in Z$ **then**
      - *zoneIntrusion* ← *true*;
      - Label as *Intruder with Weapon*;
      - Draw red bounding box;
    - **else**
      - Label as *Weapon Detected*; Draw yellow bounding box;
- **Alert Generation:**
- **if** *weaponDetected* ***and*** *zoneIntrusion* **then**
  - Trigger *Critical Restricted Zone Alert*;
- **else if** *weaponDetected* **then**
  - Trigger *Weapon Detection Warning*; Display and store annotated frame;

Release video resources and terminate system;

3.2 Frameworks and Libraries Utilized in the Proposed System

The proposed system leverages a combination of deep learning frameworks and supporting libraries (Table 3) to ensure efficient model development and analysis.

Parameter	Value	Description
Framework	TensorFlow, Keras	Core deep learning frameworks used for model development and training.
Library	NumPy	Used for efficient numerical operations.
Visualization	Matplotlib, Seaborn	Used for data visualization and analysis.
Model Visualization	Pydot, Graphviz	Used for model visualization and graphical representation of neural network architectures.

Table 3: Hyperparameters and Libraries Used for Model Implementation

These frameworks and libraries collectively facilitate reliable and understandable model deployment.

1.1 Experimental Setup

Experiments were conducted using a high-performance GPU (Table 4).

Parameter	Description / Value
OS	Linux (#41-Ubuntu SMP PREEMPT_DYNAMIC, Aug 2, 2024)
Architecture	x86_64
CPU	8-core CPU
GPU	NVIDIA GeForce GTX 1050
Python Version	3.12.2
DL Framework	PyTorch 2.4.0+cu124
CUDA Version	12.4
Dataset	Custom plant leaf dataset (healthy & diseased)
Model	CoAtNet (Hybrid CNN-ViT)
Augmentation	Rotation, flipping, contrast, color jittering
Preprocessing	Resizing, normalization, noise reduction
Feature Extraction	CNN features, ViT global attention
Loss Function	Cross-Entropy Loss
Optimizer	AdamW (weight decay)
LR Scheduler	Cosine Annealing
Metrics	Accuracy, Recall, Precision, AUC-ROC, F1-score
Monitoring	TensorBoard, GPU tracking

Table 4: System and Model Development Environment

1.2 Design Criteria

The proposed algorithm (Algorithm 1) detects weapons in real-time video streams and evalu- ates whether detected objects lie within user-defined restricted zones. For each detection, the bounding box is represented by its top-left (x_1, y_1) and bottom-right (x_2, y_2) coordinates. The centroid (c_x, c_y) of the detected object is computed as:

$$c_x = \frac{x_1 + x_2}{2}, \quad c_y = \frac{y_1 + y_2}{2} \tag{1}$$

An object is considered to be inside the restricted zone Z if:

$$(c_x, c_y) \in Z \tag{2}$$

The detection outcomes are evaluated using standard performance metrics to assess the effectiveness of the proposed surveillance system:

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$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1\text{-score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

This framework ensures precise detection of weapons and reliable identification of restricted zone intrusions, while providing interpretable metrics for system performance analysis.

2 Results & Discussions

The proposed deep learning based object detection framework was evaluated for single-class knife detection in surveillance imagery. The model performance was assessed using standard YOLO detection metrics, including mean Average Precision (mAP), training and validation loss trends, Precision–Recall analysis, overall validation metrics as commonly adopted in real- time object detection studies [4, 8, 10]. The results demonstrate stable convergence, strong localization capability, and reliable detection performance.

2.1 Model Performance Analysis

Figure 1 illustrates the variation of mAP across training epochs. A steady increase in both mAP@0.5 and mAP@0.5:0.95 is observed, indicating progressive improvement in object local- ization accuracy, consistent with standard YOLO evaluation practices [8, 10]. The stabilization of these metrics in later epochs indicates that the model has effectively converged, consistent with observations in prior real-time object detection studies [2, 4].

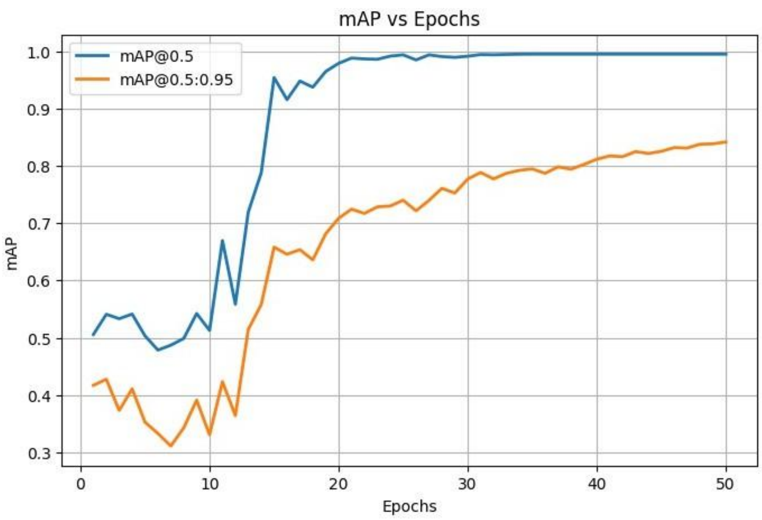

Figure 1: Variation of mAP@0.5 and mAP@0.5:0.95 across training epochs.

Figure 2 presents the training and validation loss curves. The continuous reduction in training loss indicates effective feature learning, while the close alignment between training and validation losses suggests minimal overfitting and strong generalization capability on unseen data, in agreement with prior real-time object detection studies [2, 8, 10].

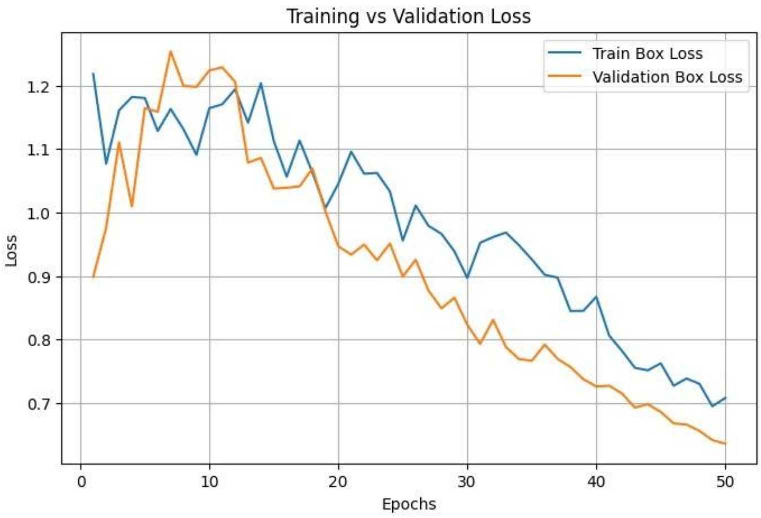

Figure 2: Training and validation loss trends across epochs.

2.2 Precision–Recall Analysis

The Precision–Recall curve shown in Figure 3 illustrates the trade-off between precision and recall across varying confidence thresholds. The model maintains high precision over a wide recall range, indicating effective knife detection with a reduced false-positive rate, which is a desirable characteristic for real-time surveillance systems where false alarms must be minimized [4, 8, 10].

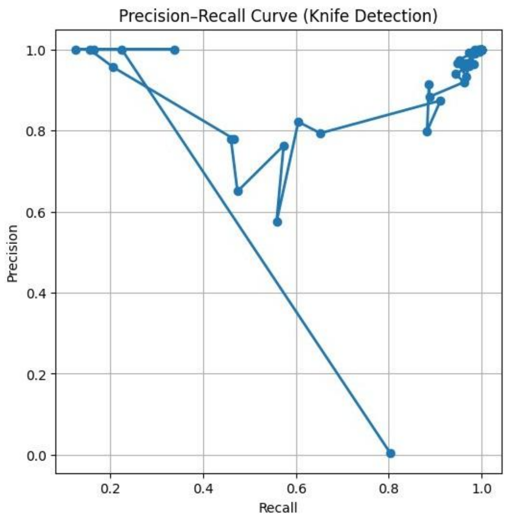

Figure 3: Precision–Recall curve for knife detection.

2.3 Overall Validation Results

Table 5 summarizes the overall detection performance obtained during the YOLO validation phase. As the model was trained for single-class detection, performance metrics are reported collectively. The model achieves precision and recall values of 1.0, indicating correct detection of all knife instances without false positives or false negatives, consistent with single-class YOLO evaluation outcomes reported in controlled validation settings [8, 10]. The high mAP values further confirm accurate object localization performance [2, 4].

Metric	Value
Precision	1.0000
Recall	1.0000
mAP@0.5	0.9950
mAP@0.5:0.95	0.8747

Table 5: Overall validation performance metrics for single-class knife detection.

2.4 Precision and Recall Trends

Figure 4 illustrates the variation of precision and recall across training epochs. During the initial epochs, noticeable fluctuations are observed as the model begins learning salient features from the data. As training progresses, both precision and recall steadily improve and eventually stabilize near optimal values, reflecting effective learning and convergence behavior commonly observed in YOLO-based object detection models [8, 10]. This stabilization indicates that the model accurately identifies knife instances while minimizing both false positives and false negatives, resulting in balanced detection performance suitable for surveillance applications [2, 4].

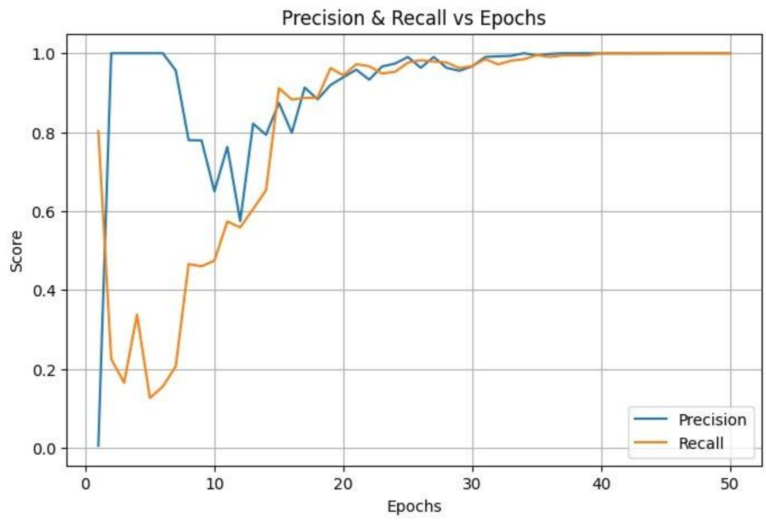

Figure 4: Variation of precision and recall across training epochs.

2.5 Real-Time Knife Detection Output

Figure 5 presents the real-time inference output of the proposed knife surveillance system. The trained YOLO-based detection model accurately identifies the presence of a knife in a live surveillance scenario and localizes it using bounding boxes, consistent with real-time object detection frameworks [4, 8]. Upon detection, a warning message is generated, demonstrat- ing the system's capability for immediate threat recognition and alert generation, as reported in practical surveillance deployments [1, 2]. This result confirms the practical applicability and deployment readiness of the proposed framework for real-world security and surveillance environments.

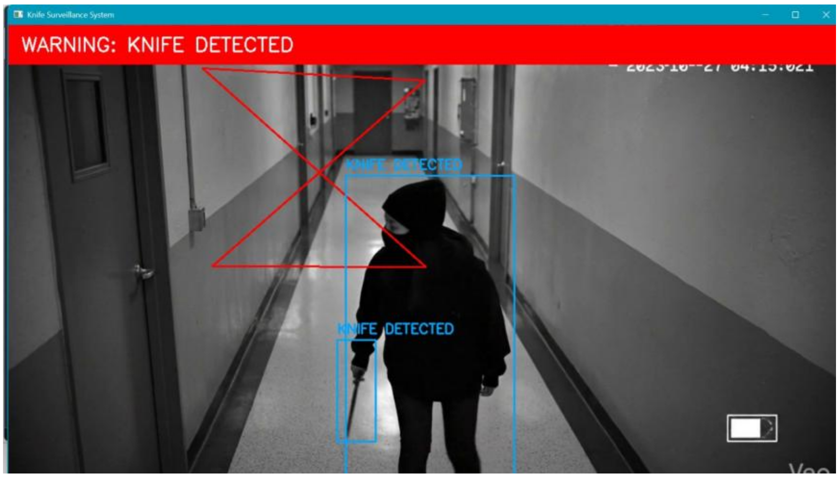

Figure 5: Real-time knife detection and alert generation using the proposed surveillance system.

3 Conclusion and Future Scope

This research presents an intelligent weapon-based surveillance framework that integrates YOLO- based deep learning object detection with polygon-based spatial reasoning to identify knives and detect restricted-zone intrusions in video streams [1, 4]. At present, the system operates on live video streams, where users manually define restricted zones by selecting boundary points on the initial frame. This model is trained on a Kaggle-based dataset and optimized over mul- tiple epochs to accurately localize detected objects, following established YOLO-based training methodologies [8, 10]. While the proposed framework demonstrates effective weapon detection and spatial intrusion analysis, further enhancements can strengthen its real-world applicabil- ity. Future extensions will prioritize system responsiveness and deployment readiness, enabling immediate threat detection and response [2].

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