Automated Weapon Detection Using YOLOv12, EfficientNetB0, and Grad-CAM

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***Abstract*—With the increasing demand for enhanced public safety and rapid threat detection, the development of intelligent weapon detection systems became essential. Traditional security methods, such as manual surveillance and basic sensor-based monitoring, often proved inadequate in dynamic, high-risk environments. This research proposed an automated weapon detection system designed to analyze uploaded images for the detection and classification of weapons. The system incorporated the YOLOv12 deep learning framework for object detection, in conjunction with the EfficientNetB0 classifier to improve accuracy and efficiency. The YOLOv12 model, selected for its advanced object detection capabilities, was trained on a custom dataset to recognize various weapon types. Subsequently, the EfficientNetB0 model was utilized to classify the detected weapons. In addition, Gradient-weighted Class Activation Mapping (Grad-CAM) was integrated to generate visual explanations of the model's predictions, enhancing interpretability and transparency. The system was evaluated using standard performance metrics, including mean Average Precision (mAP), Intersection over Union (IoU), precision, recall, and inference speed (FPS). The results validated the system's effectiveness in accurately detecting and classifying weapons from image inputs, offering a scalable approach for real-time threat analysis in public safety applications.**

Keywords— YOLOv12, Grad-CAM, deep learning, weapon detection, object detection, public safety, image-based detection.

I. Introduction

The increasing need for enhanced public safety and security has made automated weapon detection a critical component of modern surveillance systems. Traditional security measures, such as manual monitoring or basic sensor-based systems, have often been costly, difficult to scale, and prone to human error. These methods have generally proven ineffective in dynamic, high-risk environments where threats may emerge unexpectedly. As urban areas have continued to grow, the ability to deploy intelligent, real-time threat detection systems capable of analyzing visual data quickly and accurately has become increasingly important for preventing incidents and ensuring public safety [1].

Recent advancements in deep learning and computer vision have revolutionized the field of object detection, enabling machines to autonomously recognize and classify various objects with high accuracy. Among these models, the YOLO (You Only Look Once) series has stood out due to its balance of speed and precision, making it well-suited for real-time object detection tasks. YOLOv12, the most recent iteration, introduced several enhancements, including improved feature fusion techniques and better handling of small, occluded, or overlapping objects [2]. These characteristics have proven particularly effective for weapon detection in complex environments where threats may be partially concealed or located in crowded scenes [3].

This research proposed an automated weapon detection system that utilized the YOLOv12 deep learning framework to detect potential threats in images. Unlike conventional approaches, the system analyzed uploaded images to identify and classify weapons with high precision, leveraging YOLOv12's superior performance in recognizing a diverse range of objects, including firearms, knives, and other weapons. By incorporating YOLOv12, the system benefited from enhanced processing speed and robust detection capabilities, rendering it suitable for real-world applications requiring timely threat identification [4], [5].

For the classification task, three state-of-the-art models were evaluated: the Vision Transformer (ViT), the EfficientNetB0 classifier, and ResNet50. Each model offered distinct advantages: ViT utilized self-attention mechanisms but required significant computational resources [6]; ResNet50 employed a deep residual learning architecture that facilitated effective training of deeper networks [7]; and EfficientNetB0 balanced accuracy with computational efficiency [8]. After training on the same dataset, the EfficientNetB0 classifier achieved the best performance in weapon classification tasks while maintaining lower resource requirements, making it suitable for practical deployment.

To improve model interpretability, the system integrated Gradient-weighted Class Activation Mapping (Grad-CAM), a widely adopted Explainable AI (XAI) method. Grad-CAM generated visual heatmaps that highlighted image regions influencing the classifier's decisions, offering insights into the model's reasoning process [9]. Such visual explanations were especially valuable in security settings, where understanding the rationale behind predictions is essential for validation and trust [10], [11].

The proposed system was evaluated using standard performance metrics, including mean Average Precision (mAP), Intersection over Union (IoU), precision, recall, and inference speed (FPS). These metrics measured the accuracy of weapon detection, the minimization of false positives, and the system's efficiency—key requirements for real-time deployment. The results indicated that the system effectively identified weapons across various real-world conditions while maintaining high

processing speed, demonstrating its applicability to public safety scenarios [12], [13].

In summary, this study introduced a novel automated weapon detection system that integrated YOLOv12 for object detection, the EfficientNetB0 classifier for risk classification, and Grad-CAM for explainability. The system provided a scalable, accurate, and interpretable solution capable of analyzing static visual inputs. This approach showed strong potential for improving public safety by enabling real-time insights into potential threats in critical environments such as airports, educational institutions, and crowded public areas.

II. Literature Survey

Recent advancements in deep learning and computer vision significantly enhanced the capabilities of automated weapon detection systems. Object detection, in particular, experienced breakthroughs with models such as YOLO, which localized and classified objects in a single forward pass, making it suitable for real-time applications. YOLOv4 [4] and YOLOv5 [5] improved detection accuracy, particularly in complex environments, and inspired further research in security systems. The latest YOLOv12 version [2] introduced advancements in feature fusion and small object detection, making it ideal for weapon detection in public spaces.

Weapon detection using deep learning models was explored in several studies. Zhu et al. [12] applied YOLO for firearm detection in crowded spaces, highlighting its efficiency. Similarly, Zhao et al. [13] demonstrated the effectiveness of YOLO in detecting weapons in public transportation systems. Other researchers, such as Nguyen et al. [14], focused on leveraging YOLO for detecting firearms in surveillance footage, achieving high accuracy in dynamic environments.

For classification tasks, models such as the Vision Transformer (ViT) [6], the EfficientNetB0 classifier [8], and ResNet50 [7] were widely adopted. ViT demonstrated exceptional performance in complex image classification tasks [6], while the EfficientNetB0 classifier achieved a balance between accuracy and computational efficiency [8]. ResNet50's deep residual learning architecture made it a widely used choice for various vision-based tasks, including weapon classification [7].

The application of Grad-CAM [9] played a pivotal role in enhancing the transparency and interpretability of object detection systems. Grad-CAM visualized the regions in an image that most influenced the model's decision, thereby improving the explainability of weapon detection outputs. Selvaraju et al. [9] introduced Grad-CAM, and subsequent studies [10], [11] investigated its application in safety-critical domains such as weapon detection.

Datasets used to train these models have also been the subject of research. The MS COCO dataset [15] and ImageNet [16] were commonly used for object detection and classification tasks. Custom datasets for weapon detection, including the GunDetection dataset [17], proved essential for training models to identify firearms and knives in real-world scenarios, as described earlier.

Other studies investigated the integration of YOLO-based systems with edge devices and cloud computing to develop scalable and efficient solutions for public safety [18], [19]. These systems enabled real-time surveillance without heavy reliance on physical sensors, making them adaptable to a variety of environments. Furthermore, IoT-based approaches were explored by Lee et al. [20] to enhance real-time feedback in surveillance systems.

In summary, the growing body of literature highlighted the potential of YOLO for weapon detection in security systems, with improvements in classification accuracy provided by models such as the EfficientNetB0 classifier. The use of Grad-CAM for model interpretability and the real-time deployment of these models through edge and cloud technologies ensured that automated weapon detection could be both effective and explainable.

III. Related Work

Early weapon detection systems predominantly relied on traditional image processing techniques such as edge detection, color histogram analysis, and background subtraction [15]. Although computationally efficient, these methods encountered significant challenges in complex and dynamic environments characterized by varying lighting conditions, occlusions, and multiple camera angles.

The introduction of deep learning advanced weapon detection capabilities considerably. Convolutional Neural Networks (CNNs), including architectures such as VGG16, ResNet, and AlexNet [7], were employed extensively for feature extraction and classification. These models demonstrated improved detection accuracy compared to traditional approaches. However, they required large annotated datasets and lacked end-to-end detection and classification capabilities, thereby limiting their real-time applicability.

In subsequent developments, object detection frameworks such as Faster R-CNN [23] and Single Shot Multibox Detector (SSD) [24] were adopted for real-time weapon detection tasks. While Faster R-CNN offered high accuracy, it remained computationally intensive, which restricted its deployment in real-time systems. SSD provided faster inference speeds but underperformed in detecting small or partially occluded weapons—challenges frequently encountered in crowded scenes.

The YOLO (You Only Look Once) family of models represented a significant advancement in real-time object detection by effectively balancing speed and accuracy. YOLOv4 [4] and YOLOv5 [5] were widely applied in weapon detection scenarios with promising results. The latest iteration, YOLOv12 [2], introduced advanced features such as improved feature fusion mechanisms, adaptive anchor box selection, and enhanced detection layers. These enhancements positioned YOLOv12 as a strong candidate for precise, real-time weapon detection applications.

Given the safety-critical nature of weapon detection, Explainable Artificial Intelligence (XAI) has gained increasing importance. Grad-CAM (Gradient-weighted Class Activation

Mapping) [9] emerged as a prevalent XAI technique that produces visual explanations by highlighting image regions influencing the model's decisions. Initially applied in domains such as medical imaging [21] and autonomous driving [11], Grad-CAM has recently been extended to weapon detection to improve system transparency and user trust.

Despite progress in deep learning-based weapon detection, the integration of XAI techniques remains relatively limited. Most existing systems prioritized performance metrics such as accuracy and precision while often overlooking interpretability—an essential requirement in security-focused applications. Recent studies, such as that by Liu et al. [22], explored the combination of YOLO models with Grad-CAM to generate interpretable visual explanations alongside high-accuracy detection.

Several works examined the synergy between deep learning models, edge computing, and cloud infrastructure to enhance the scalability and efficiency of real-time weapon detection systems. For example, Lee et al. [20] investigated the deployment of YOLO-based models on edge devices to accelerate inference, while Geng and Cassandras [25] proposed cloud-based surveillance frameworks for real-time monitoring. This convergence of IoT devices and cloud computing emerged as a pivotal factor in enabling scalable public safety solutions that demand prompt threat identification.

In summary, recent research highlighted the effectiveness of YOLO-based architectures—particularly YOLOv12—in delivering high-accuracy, real-time weapon detection. The incorporation of XAI methods such as Grad-CAM further enhanced these systems by improving interpretability and trustworthiness. These integrated approaches enabled the development of robust, transparent, and scalable weapon detection systems suitable for deployment in complex real-world environments where timely threat recognition is critical.

IV. Methodology

The proposed system was designed to detect and classify weapons in real-world images, addressing practical challenges such as occlusions and varying lighting conditions. Although the dataset included images containing multiple weapons, the system demonstrated optimal performance on single-weapon instances. The approach integrated object detection using YOLO models, classification through deep learning architectures, and visual explanation techniques via Grad-CAM to enhance interpretability. The methodology was structured into distinct phases to ensure clarity and reproducibility.

A. Environment Setup and Library Configuration

The experimental environment was configured in *Google Colab* with GPU acceleration to expedite computational processes during training and evaluation. Both the TensorFlow and PyTorch frameworks were employed to support object detection and classification tasks.

Installed Libraries:

- **PyTorch** and **torchvision** for training and inference with the YOLOv5, YOLOv8, and YOLOv12 models.
- **TensorFlow** for implementing the ResNet50 and the EfficientNetB0 classification models.
- **opencv-python**, **matplotlib**, and **seaborn** for image preprocessing and result visualization.
- **albumentations** for applying image augmentation techniques.
- **Grad-CAM** for generating visual explanations of the classification decisions.

This configuration ensured compatibility with state-of-the-art deep learning techniques and leveraged GPU-based acceleration for efficient model development and execution.

B. Dataset Acquisition and Preparation

A custom dataset comprising real-world weapon images, often containing multiple weapons per frame, was employed in this study. Each image was annotated using YOLO-format text files, which included bounding boxes and class labels corresponding to nine weapon categories.

Dataset Format:

- The dataset adhered to YOLO annotation standards and included a structured `data.yaml` configuration file to facilitate integration with the training pipeline.
- Annotations consisted of bounding box coordinates and class identifiers for each detected weapon.

Dataset Statistics: The dataset contained over 700 training images and 140 validation images. The total number of object instances per class is summarized in Table I. Each class corresponded to a specific weapon type, as detailed below:

Table I. *Class Distribution of Weapons in Train and Validation Sets*

Class ID	Weapon Class	Train Samples	Val Samples
0	Automatic Rifle	125	20
1	Bazooka	65	16
2	Grenade Launcher	80	24
3	Handgun	121	38
4	Knife	139	19
5	Shotgun	96	22
6	SMG	117	28
7	Sniper	85	30
8	Sword	108	22

Preprocessing Steps:

- **Resizing:** All input images were resized to 480×480 pixels to maintain uniformity across the dataset.
- **Normalization:** Pixel values were normalized to the range [0, 1] to facilitate stable model training.
- **Data Augmentation:** To improve generalization, the following transformations were applied:
  - Horizontal and vertical flipping
  - Mosaic augmentation (combining four images into one)
  - HSV-based color jittering
  - Random scaling, shifting, and rotation

The dataset was partitioned into training (70%), validation (20%), and testing (10%) subsets. Labels were stored in the YOLO text format, aligned with the corresponding image filenames. The dataset structure was defined using a

`data.yaml` file to ensure compatibility with YOLO-based detection frameworks.

C. YOLO Detection Model Training

Three YOLO variants—YOLOv5, YOLOv8, and YOLOv12—were evaluated for the task of weapon detection in static images. YOLOv5 and YOLOv8 are officially released and widely adopted models, whereas YOLOv12 refers to an unofficial implementation available on GitHub (https://github.com/sunsmarterjie/yolov12). As of May 2025, YOLOv12 had not been formally published in peer-reviewed literature; however, it introduced architectural enhancements aimed at improving detection under challenging conditions, such as occlusion and overlapping objects.

For this study, the YOLOv12 repository was cloned, and the pre-trained weights (`yolov12x.pt`) were used. All models were trained and evaluated in the Google Colab environment. As shown in Table II, YOLOv8 achieved the highest detection accuracy (mAP@0.5 = 0.8646) and the shortest training time. Nonetheless, YOLOv12 provided a favorable balance between detection performance and interpretability. Its architecture was more suitable for integrating explainability tools such as Grad-CAM, which facilitated the visualization of activation regions corresponding to hidden or occluded weapons. Therefore, YOLOv12 was selected for final deployment in this study.

Dataset Configuration: The training and validation datasets were organized in a YOLO-compatible format. A `data.yaml` file defined the dataset structure, including the paths for training and validation images, along with a list of weapon classes: Automatic Rifle, Bazooka, Grenade Launcher, Handgun, Knife, Shotgun, SMG, Sniper, and Sword.

Environment Setup: The training environment was configured with the necessary libraries, including `ultralytics`, `torch`, `torchvision`, and `albumentations`. The YOLOv12 repository was cloned, and the pre-trained `yolov12x.pt` model was downloaded for fine-tuning. A GPU-enabled setup was employed to accelerate computations.

Training Configuration:

- Pre-trained Model: `yolov12x.pt`
- Epochs: 70
- Batch Size: Default (based on YOLOv12 repository settings)
- Optimizer: SGD (default for YOLO models in Ultralytics framework)
- Image Size: 480×480
- Device: CUDA-enabled GPU
- Data Augmentation: Horizontal flips, mosaic augmentation, HSV variations, scaling, and rotation.

The training process utilized the Ultralytics `YOLO` API, which enabled an efficient and robust fine-tuning workflow. These configurations enhanced the model's capability to detect weapons under diverse real-world conditions, including cluttered and complex backgrounds.

D. Classification Model Training

To categorize the detected weapons, three classification models were trained:

- **ResNet50** (TensorFlow)
- **Vision Transformer (ViT)** (PyTorch)
- **the EfficientNetB0 model** (PyTorch)

The EfficientNetB0 model was selected for deployment due to its lightweight architecture and high classification accuracy.

Training Configuration:

- Optimizer: Adam
- Batch Size: 32
- Learning Rate: 1×10^{-4}
- Image Size: 224×224
- Loss Function: Cross-Entropy Loss
- Augmentation: Resizing, normalization, and horizontal flips
- Number of Epochs: 10

The classification pipeline efficiently categorizes weapons into predefined classes with high accuracy and reliability.

E. Model Evaluation and Performance Metrics

The system employed robust metrics to evaluate both detection and classification models:

Detection Evaluation:

- **mAP@0.5:** Precision at IoU $= 0.5$.
- **mAP@0.5:0.95:** Aggregated precision across IoU thresholds.
- Precision, Recall, and F1-score.

Classification Evaluation:

- **Accuracy:** Percentage of correctly classified weapons.
- **Precision and Recall:** Class-specific performance metrics.
- **F1-score:** Balances precision and recall.
- **Confusion Matrix:** Visualizes misclassifications.

These metrics provide a comprehensive understanding of system performance.

F. Detection and Visualization of Predictions

The system processed test images to detect and classify weapons. The visualization included:

- **Bounding Boxes:** Generated for each detected weapon, annotated with class labels and confidence scores.
- **Color Coding:** Green indicated high-confidence predictions, while red represented uncertain or incorrect detections.

A user-friendly interface was provided to enable testing with custom images and real-time visualization of results.

G. Explainable AI via Grad-CAM

To enhance interpretability, **Grad-CAM** was integrated with the EfficientNetB0 classifier. Grad-CAM highlighted image regions that influenced classification decisions.

Explainability Process:

- Heatmaps were generated overlaying the detected weapon regions.

- The heatmaps were normalized and blended with the original images.
- Visual explanations were provided for each classification decision.

This step ensured that users and developers could understand and validate the system's predictions, thereby increasing trust and usability.

H. Comparison of Models

A detailed comparison of detection and classification models was conducted to ensure the selection of the best-performing models. Tables II and III summarize the performance of the YOLO-based object detectors and the CNN-based classifiers, respectively.

Table II. *Performance Comparison of YOLO Models on Weapon Detection Dataset*

Model	mAP@0.5	mAP@0.5–0.95	Precision	Recall
YOLOv5	0.7900	0.5570	0.7360	0.7860
YOLOv8	**0.8646**	**0.6995**	**0.8615**	**0.7981**
YOLOv12	0.8153	0.6569	0.8606	0.6787

Table III. *Performance Comparison of Classification Models*

Model	Accuracy	Precision	Recall	F1-Score
ViT	0.8300	0.75	0.83	0.78
EfficientNetB0	**0.8300**	**0.83**	**0.83**	**0.83**
ResNet50	0.6434	0.63	0.64	0.63

The comparisons illustrated trade-offs between model accuracy, architectural complexity, and computational efficiency. YOLOv8 demonstrated the highest detection accuracy, while YOLOv12 was selected due to its architecture being well-suited for integration with advanced modules such as Grad-CAM. Among the classification models, the EfficientNetB0 classifier delivered the best performance with a compact design, outperforming the ViT and ResNet50 models.

I. Summary and Output Reporting

All results were displayed directly within the testing environment for immediate evaluation and interpretation. The output included:

- **Real-Time Visualizations:** Detection bounding boxes and classification labels were dynamically rendered on test images.
- **Grad-CAM Heatmaps:** Explanatory overlays were generated and shown on-the-fly for each classification result.
- **Performance Metrics:** Metrics such as mAP, precision, recall, and F1-scores were computed and presented in the console output for straightforward analysis.
- **Interactive Testing:** Users were enabled to upload custom images, view real-time predictions, and observe model behavior directly within the interface.

This approach ensured a user-centric experience, emphasizing interpretability and immediate feedback without the need for file storage or post-processing.

V. Results and Evaluation

This section presented the evaluation of the proposed weapon detection and classification system. The pipeline integrated object detection using YOLOv12 and classification using the EfficientNetB0 classifier, which were trained and tested on a custom multi-weapon dataset. The evaluation included both quantitative performance metrics and qualitative visualizations, focusing on detection precision, classification accuracy, and model explainability.

A. Quantitative Evaluation Metrics

To measure the object detection performance of the YOLOv12 model, standard evaluation metrics were utilized:

- **Precision:** The proportion of correctly predicted weapon bounding boxes to all predicted boxes.
- **Recall:** The ratio of correctly predicted weapons to the actual number of weapons present.
- **F1 Score:** The harmonic mean of precision and recall.
- **mAP@0.5:** Mean Average Precision at an IoU threshold of 0.5.
- **mAP@0.5:0.95:** Mean Average Precision averaged over multiple IoU thresholds from 0.5 to 0.95.

Table IV. *Detection Performance Metrics (YOLOv12)*

Metric	Value
Precision	0.860
Recall	0.678
F1 Score	0.758
mAP@0.5	0.815
mAP@0.5:0.95	0.656

These results indicated the model's high proficiency in identifying weapons, demonstrating strong generalization across multiple object types and positions within an image.

B. Weapon Classification Accuracy

The EfficientNetB0 classifier was used to categorize detected weapons into classes such as knife, pistol, and rifle. After fine-tuning for 50 additional epochs with class weights and focal loss applied, the classification performance was evaluated using the following metrics:

- **Accuracy**
- **Precision**
- **Recall**
- **F1 Score**

Table V. *Classification Performance Metrics (EfficientNetB0)*

Metric	Value
Accuracy	0.830
Precision	0.830
Recall	0.830
F1 Score	0.830

These values confirmed the EfficientNetB0 classifier's ability to distinguish among visually similar weapons with high accuracy and a balanced precision-recall trade-off.

(a) Grad-CAM visualization 1

(b) Grad-CAM visualization 2

Fig. 1. Fig. 1. Grad-CAM visualizations illustrating model attention on weapon-relevant regions.

(a) Detection sample 1

(b) Detection sample 2

Fig. 2. Sample detections showing multiple weapons with bounding boxes.

C. Model Explainability (Grad-CAM)

To enhance model transparency and interpret the classifier's decisions, Gradient-weighted Class Activation Mapping (Grad-CAM) was applied to the output of the final convolutional layers. This technique produced heatmaps highlighting the image regions that contributed most to the model's predictions.

- **Visual Focus:** The Grad-CAM heatmaps consistently highlighted weapon-relevant areas such as barrel contours in rifles, blade edges in knives, and trigger zones in handguns, indicating that the model correctly concentrated on semantically meaningful regions.
- **Interpretability:** In cases where misclassifications occurred—such as confusing a grenade launcher with a bazooka—Grad-CAM revealed overlapping attention on similar structural regions, suggesting that visual ambiguity in features contributed to the errors.
- **Human Alignment:** Qualitative assessment by human observers confirmed that the model's attention closely aligned with intuitive decision points. For example, the presence of metallic textures and sharp outlines matched both model attention and human reasoning.

These observations affirmed that Grad-CAM not only supported interpretability but also provided diagnostic insights into classification performance, especially in visually complex or occluded scenarios.

D. Detection Results and Visual Analysis

Detection outputs were overlaid with bounding boxes and confidence scores on the test images. The system accurately detected multiple weapons within a single frame despite challenges such as occlusion, overlap, diverse weapon orientations, and varying lighting conditions as described earlier.

E. System Performance and Inference Time

The complete system was deployed on Google Colab using a Tesla T4 GPU. The average per-image processing time at 640×640 resolution was measured as follows:

- **YOLOv12 detection:** 27 ms
- **The EfficientNetB0 classifier:** 31 ms
- **Grad-CAM explainability module:** 22 ms

Total processing time: Approximately 80 ms per image.

These results confirmed the system's suitability for near real-time deployment in surveillance and security applications.

F. Summary of Findings

The integration of YOLOv12 for detection and the EfficientNetB0 classifier for classification yielded an accurate, explainable, and efficient framework for weapon detection and categorization:

- High mAP scores were achieved for detection, even in scenes containing multiple weapons.
- Strong classification performance was obtained, with a high F1 score.
- Interpretability was provided through Grad-CAM visualizations.
- Practical inference times were demonstrated for real-world applications.

This pipeline provided a valuable foundation for real-time surveillance, law enforcement support systems, and smart security infrastructure.

VI. Use Cases and Applications

The deep learning-driven weapon detection and classification system proposed in this study demonstrated significant potential for real-world security and surveillance applications. By utilizing YOLOv12 for real-time object detection and the EfficientNetB0 classifier for precise classification, the framework addressed essential security challenges across various sectors:

- **Public Safety and Law Enforcement:** The system was designed for implementation in high-traffic public areas such as transportation hubs, government buildings, and large-scale events to automatically identify and categorize weapons in real time. This proactive approach enabled law enforcement agencies to respond swiftly to potential threats and reduce reaction times during emergencies.
- **Smart City Surveillance Systems:** When integrated with existing CCTV networks in smart cities, the technology provided continuous automated monitoring for weapon threats, thereby strengthening urban security and alleviating the workload of human personnel.
- **Access-Controlled Facilities:** High-security environments, including data centers, airports, and military sites, leveraged the system to incorporate weapon detection into

access control processes, facilitating real-time screening and classification without requiring manual inspections.

- **Support for Threat Analysis and Forensic Investigation:** Grad-CAM visualizations enhanced transparency by highlighting regions of an image that most influenced the model's classification decision. This feature supported security experts and investigators during post-event analysis and fostered greater trust in the model's outputs.
- **Crowd Surveillance and Event Security:** During large public gatherings or festivals, the system was deployed to monitor crowds for visible weapons, providing a scalable and automated solution to augment the capabilities of on-site security teams.

In conclusion, the proposed system presented a scalable, efficient, and interpretable solution for weapon detection and classification. Its implementation was shown to improve proactive threat management and could play a vital role in modern surveillance and security infrastructures.

VII. Limitations

While the YOLOv12-based weapon detection and the EfficientNetB0 classification framework demonstrated promising results, several challenges were observed during real-world testing and evaluation:

- **Lighting and Environmental Factors:** The model's performance degraded under conditions with insufficient lighting, glare, shadows, or reflections, occasionally resulting in false positives or missed detections.
- **Obscured or Partial Visibility:** Detection accuracy decreased when weapons were partially concealed by other objects or clothing, or held in unusual positions, particularly for smaller or hidden weapons.
- **Generalization to New Weapon Types:** The classification model struggled to identify weapons not included in the training data, leading to misclassifications or low-confidence results.
- **Hardware and Real-Time Constraints:** Deployment on edge devices or systems with limited computational power caused delays or reduced frame rates. Techniques such as model compression or quantization were identified as necessary to enable real-time processing.
- **Challenges in Interpretability:** Although Grad-CAM improved model interpretability, its heatmaps were sometimes overly general or highlighted irrelevant regions, complicating precise identification of factors influencing the model's decisions.

Future work may focus on enhancing robustness in adverse conditions, expanding the dataset to include a wider variety of weapon types, refining Grad-CAM visualizations through alternative interpretability methods, and optimizing the model for deployment on resource-constrained devices.

VIII. Conclusion

This research proposed an AI-driven weapon detection and classification framework combining YOLOv12 for real-time object detection and the EfficientNetB0 classifier for detailed weapon classification. The system aimed to improve public safety and surveillance by detecting and localizing weapons in visual data without manual oversight.

The framework was trained and tested on a diverse dataset containing various weapon types, including images featuring multiple weapons per frame, partial occlusion, and diverse lighting conditions. YOLOv12 demonstrated strong detection accuracy and localization, while the EfficientNetB0 classifier achieved high classification performance. Grad-CAM visualizations further enhanced model interpretability.

The proposed system was scalable, efficient, and adaptable, making it suitable for various security applications, from public surveillance to edge-based monitoring devices. The integration of explainable AI added transparency and trust to the decision-making process.

Future developments will include expanding the dataset to cover more weapon types and real-world contexts, enhancing model robustness under challenging conditions, optimizing deployment on low-power devices, and integrating temporal analysis for continuous threat assessment.

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