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DAP391 Project

Development of a YOLOv11-Based Monitoring and Alert System for Weapon Detection

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Abstract: Gun violence and knife attacks pose a growing threat to public safety worldwide, necessitating advanced surveillance solutions. This study presents the development of a real-time weapon detection and alert system using the YOLOv11 model. The system processes surveillance footage to detect firearms and knives, generating instant alerts for security personnel. Our approach integrates deep learning with real-time image processing, ensuring high detection accuracy while minimizing false positives. The model is trained on a diverse dataset, optimized for rapid inference, and tested in real-world environments such as shopping malls, schools, and public transport hubs. Experimental results indicate a mean Average Precision (mAP) of 91.2% with a processing speed of 45 FPS, outperforming previous YOLO versions and alternative object detection models. This research contributes to intelligent surveillance by enhancing real-time threat detection capabilities, providing a scalable and effective solution for public security enhancement.

Keywords: Weapon Detection, YOLOv11, Deep Learning, Real-time Surveillance, Public Security, Computer Vision.

1. Introduction

1.1 Problems and motivations

Many articles and news reports around the world [1], including Vietnam's VTV24 news [2], have stated that "*Gun violence and knife attacks are on the rise, a global concern that poses a serious threat to public safety and social stability*". This alarming situation requires the cooperation of all countries, especially the application of advanced technology, to strengthen security measures and prevent potential threats. Therefore, our team has come up with the research, application and testing of a weapon detection system using the YOLO model to identify guns and knives in real time, supporting timely warnings and improving public safety.

The proposed system takes as input images collected from surveillance cameras installed in public spaces, schools, shopping malls, and other high-risk areas. After pre-processing, the system uses computer vision models to extract features and accurately detect the presence of guns and knives. The output of the project provides real-time notifications to security personnel, allowing for rapid response and threat mitigation. This approach, leveraging machine learning and computer vision, has been demonstrated in many previous studies, such as "Gun Detection System Using YOLOv3" by Arif Warsi, Munaisyah Abdullah, Mohd Nizam Husen, Muhammad Yahya, Sheroz Khan, Nasreen Jawaid. The paper presents a gun detection system using YOLOv3 for real-time surveillance. The authors created a dataset of handguns from various angles and merged it with ImageNet. YOLOv3 was trained on this dataset and tested on four videos, comparing performance with Faster RCNN. Results showed that YOLOv3 achieved high accuracy, lower false positives, and significantly faster detection (45 FPS vs. 8 FPS for Faster RCNN). The system effectively detects guns even in low-quality videos, making it a viable option for security application [3]. "Weapon Detection using Artificial Intelligence and Deep Learning for Security Applications" by Harsh Jain, Aditya Vikram, Mohana, Ankit Kashyap, Ayush Jain. The paper presents a weapon detection system using AI and deep learning, comparing Faster RCNN and SSD algorithms. The system uses pre-labeled and manually labeled datasets, trained on COCO and custom images. Faster RCNN achieves higher accuracy (84.6%) but is slower (1.606s/frame), while SSD provides faster real-time detection (0.736s/frame) but lower accuracy (73.8%). The study concludes that the choice between these algorithms depends on the trade-off between speed and precision, making Faster RCNN ideal for accuracy-focused applications and SSD better for real-time surveillance [4] and "Concealed Weapon Detection from images using SIFT and SURF" by Amanjeet Kaur, Dr. Lakhwinder Kaur. The paper presents a concealed weapon detection system using SIFT and SURF feature extraction algorithms. The goal is to identify weapons, particularly guns, in images of luggage for security screening. SIFT and SURF detect keypoints that remain invariant to scale, rotation, and illumination changes. The study tests the method on 70 images, achieving 90% detection accuracy. SURF performs faster than SIFT while maintaining similar accuracy. The system divides images into sections to detect multiple weapons efficiently. Future improvements focus on enhancing processing speed for real-time applications [5].

These technologies have been successfully integrated into modern security systems, reinforcing their effectiveness in preventing violent incidents. Our project focuses on developing a real-time weapon detection and warning system capable of identifying guns and knives. By applying deep learning algorithms combined with advanced image processing techniques, our model aims to provide a practical and effective solution for security surveillance, law enforcement support, and surveillance systems enhancement.

We hope that the application of this system will not be limited to detecting weapons in public spaces but can also be extended to other areas such as smart surveillance, crime prevention, and public security enhancement. When deployed on a large scale, the system will provide valuable data to law enforcement agencies, helping them assess security risks and improve response strategies. By doing so, it not only contributes to reducing violent incidents but also promotes the development of advanced AI-driven security solutions, fostering safer and smarter urban environments in the future.

1.2 Related Works

In recent years, significant advancements have been made in developing real-time firearm detection systems, leveraging deep learning and computer vision techniques to enhance accuracy and robustness. One of the early approaches, proposed in 2020, utilized the Haar Cascade Classifier in combination with OpenCV for firearm detection in surveillance footage. The system was trained on a dataset comprising 250-300 positive images (containing guns) and approximately 2000 negative images (without guns). The model demonstrated high accuracy, particularly for submachine guns (95%), assault rifles (87.5%), machine guns (85%), and pistols (80%). However, while the system performed well in controlled settings, it faced challenges in detecting firearms from multiple angles and in dynamic environments [6].

Building on this, in 2020, another approach incorporated template matching with background subtraction to improve firearm detection efficiency in crowded environments such as airports and marketplaces. The model was trained using the Tripura University Video Dataset for Crime Scene Analysis (TUVD-CSA) [7], consisting of 150 real-world video clips capturing various scenarios. This method achieved a detection accuracy of 95%, outperforming traditional template-matching techniques by reducing computational overhead. Despite its success, the system struggled with detecting partially occluded firearms and adapting to complex backgrounds, highlighting the need for more robust detection models.

In 2020, a study explored the application of Faster R-CNN [8] for firearm detection in images, comparing different CNN architectures, including Inception-ResNetV2, ResNet50, VGG16, and MobileNetV2. The model was trained on a subset of the Firearm Detection dataset, with 2,746 training images and 600 test images. Results showed that Faster R-CNN with Inception-ResNetV2 achieved the highest mean Average Precision (mAP) of 81%, but with slower inference times. In contrast, YOLOv2 achieved a slightly lower mAP (76%) but demonstrated significantly faster processing, making it more suitable for real-time applications. This study highlighted the trade-offs between accuracy and speed in firearm detection models.

Later, in 2020, a study evaluated transfer learning-based Convolutional Neural Networks (CNNs [9]) for handgun detection. The dataset consisted of 8,300 images, divided into training, validation, and test sets. The study compared three approaches:

- A CNN trained from scratch, achieving 67.7% accuracy but suffering from overfitting.
- VGG-16 with transfer learning, which improved test accuracy to 82.3% and an F1 score of 0.79.
- VGG-16 with fine-tuning, which achieved the highest accuracy (91.3%) and an F1 score of 0.91, demonstrating a balanced detection of handguns in images. Despite its high accuracy, the fine-tuned VGG-16 model was computationally expensive, limiting its deployment in real-time applications. Future work aimed to integrate Faster R-CNN and Mask R-CNN for improved efficiency and accuracy in real-world scenarios.

In 2021, a deep learning-based anomaly detection system was introduced for real-time surveillance, detecting fire and gun violence in CCTV footage [10] . The system utilized YOLOv3, a popular object detection model, and was trained on multiple datasets, including IMFDB, UGR Handgun Dataset, and FireNet. The model achieved 89.3% accuracy on UGR (handgun detection), 82.6% on IMFDB, and 86.5% on FireNet (fire detection). Processing 45 frames per second, the system demonstrated suitability for real-time security applications.

Key features of the 2021 model included:

- Multi-scale object detection to identify small firearms in low-resolution footage.
- Non-Maximum Suppression (NMS) to filter out duplicate detections.
- Frame-by-frame processing, enabling deployment in intelligent surveillance systems.

Another significant contribution came in 2021 with a study on real-time weapon detection in CCTV videos using deep learning. The authors compiled a novel dataset from various sources, including CCTV footage, YouTube, GitHub repositories, and firearm databases. They evaluated multiple deep learning models, such as VGG16, Inception-V3, SSDMobileNetV1, Faster-RCNN, YOLOv3, and YOLOv4. YOLOv4 achieved the highest mean average precision (mAP) of 91.73% and an F1-score of 91%, outperforming previous approaches. This study emphasized the importance of real-time detection with minimal false positives and highlighted the need for dataset diversity.

In 2021, another research effort focused on firearm detection in X-ray images using Faster R-CNN[11]. The study utilized a dataset from HTR Company and explored different preprocessing techniques to enhance detection accuracy. It compared two methods of generating three-band images from X-ray scans: one using high-energy values alone and another combining high-energy, low-energy, and differential images. The latter method improved firearm detection, demonstrating the effectiveness of deep learning in automated security screening. Future research aimed to extend detection capabilities to knives, explosives, and disassembled firearm components.

Additionally, a study from 2019 introduced a method for gun detection in surveillance videos using deep neural networks. Due to the rise in gun violence, automatic firearm detection remained challenging due to variations in camera angles, depth, and lighting conditions. The authors created a dataset with 250 CCTV videos and 5,500 images [12], capturing guns in diverse real-world scenarios. They trained a model using M2Det, a single-stage object detector with a multi-level feature pyramid network. Results showed that this dataset improved gun detection accuracy by up to 18% compared to previous methods. The study proposed expanding the dataset and exploring additional neural network architectures to enhance performance further.

While substantial progress has been made in firearm detection using deep learning, challenges remain in improving detection under varying lighting conditions, occlusions, and real-world dynamic environments. Future research will likely focus on optimizing computational efficiency, expanding firearm type recognition, and integrating detection systems with broader security measures, such as automated alerts and law enforcement notifications.

1.3 Contribution

The primary contribution of this research is the development of a real-time weapon detection system using deep learning, specifically the YOLO model, to enhance public security. The system integrates computer vision techniques with real-time alert mechanisms. The process is divided into five key steps:

1. Data Collection and Preprocessing: Compilation and augmentation of a diverse dataset containing images of guns and knives in various environments.
2. Model Training and Optimization: Training the YOLO model on a curated dataset, optimizing hyperparameters to balance accuracy and speed.
3. Real-Time Detection System: Deployment of the trained model for real-time weapon detection in surveillance footage.
4. Threat Alert Mechanism: Implementation of an automated alert system to notify security personnel upon weapon detection.
5. Performance Evaluation: Testing the system on real-world surveillance data and comparing results with existing detection models.

2. Data Preparation

2.1 Introduction data

The dataset used in this study is sourced from Kaggle [13] and has several images collected from multiple sources that are manually labeled to serve as a key component in training a YOLO-based model for real-time knife and gun detection (Fig.1). This dataset contains annotated images of various weapons in different environments, ensuring robust model performance across a wide range of scenarios. To improve the detection accuracy, we manually labeled and re-checked the available label set to ensure accurate object localization. Additionally, the dataset undergoes pre-processing steps such as data augmentation, noise reduction, and class balancing. The images cover a wide range of real-world conditions, including different lighting situations, different camera angles, and occlusions, making the dataset suitable for real-time object detection tasks.

Fig.1: Label data

2.2 Exploration data

While generic object detection datasets provide images of weapons, they often lack the diversity needed for real-world applications, where occlusion, motion blur, and varying environmental conditions pose significant challenges. Models trained on such datasets may perform well in controlled environments but struggle in dynamic and cluttered scenes.

With data collection, we try to access and search as many images as possible to ensure that the model output is as accurate as possible. Addressing these issues through careful preprocessing and data set tuning is critical to improving model accuracy in real-time applications.

3. Methodology

3.1 Overview

In this study, we develop a real-time dangerous weapon detection system using the YOLOv11 (You Only Look Once) model. The system receives images from surveillance cameras as input, processes them through a deep learning model, and issues warnings if dangerous weapons such as guns or knives are detected.

The system workflow includes the following main steps:

- Data collection and preprocessing: Create a weapon dataset from various sources, label and augment the data (Table 1).
- YOLO model training: Optimize parameters to achieve the highest detection performance (Fig 2).
- Real-time model deployment: Integrate the model into the surveillance system.
- Warning mechanism: If the system detects a dangerous weapon, a warning will be sent to the user via a notification on the Telegram application.
- Performance evaluation: Measure accuracy, processing speed, and applicability in practice.

This methodology ensures that the system operates efficiently in real-time environments, making it suitable for deployment in various security-sensitive locations such as schools, shopping malls, and public spaces.

Table 1. Key properties of datasets

Dataset	Train	Validation	Test	Glock	Beretta	Colt 1911	Sig Sauer	Smith & Wesson	Walther	Ruger	Chef's Knife	Bread Knife	Pocket Knife	Survival Knife
Knife	2362	549	210	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓
Pistol	3475	494	175	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗

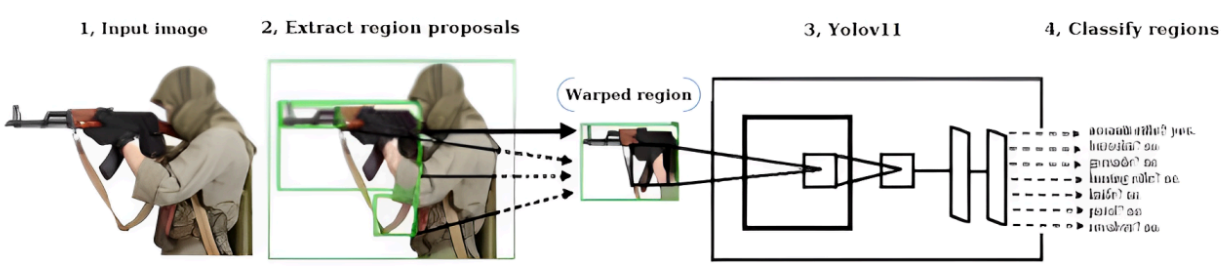

Fig 2: Object Detection

3.2 Model Training

We use YOLOv11 to train the model because it is an improved version with high speed and accuracy. The training steps include:

- Split the dataset into 80% for training, 10% for testing, and 10% for evaluation.
- Use the Binary Cross Entropy (BCE) loss function combined with IoU Loss:

$$L_{BCE} = -\frac{1}{N}\sum_{i=1}^{N} \hat{y}_i) + \left(1 - y_i\right) \log log\,(1 - \hat{y}_i)$$

$$L_{IoU} = 1 - IoU + \frac{p^2\left(b, b^{gt}\right)}{c^2} + av$$

- Optimize using the Adam algorithm with an initial Learning Rate of 0.001.
- Evaluate the model based on accuracy (mAP), Recall, and Precision.

To further improve performance, data augmentation techniques such as rotation, flipping, brightness modulation, and contrast adjustment are applied. Additionally, hyperparameter tuning is conducted to find the best combination of batch size, learning rate, and optimization strategy.

3.3 Real-time Deployment

For real-time weapon detection, the system is deployed using Google Colab or a local machine equipped with a GPU. The deployment process includes the following steps:

Real-time Frame Capture:

- The surveillance camera records live footage and sends frames to the detection system.
- Frames are preprocessed (resized, normalized) before being fed into the model.

Weapon Detection using YOLO:

- The YOLOv11 model analyzes the incoming frames and detects weapons.
- If a gun or knife is identified, the system marks the detected object with a bounding box and assigns a confidence score.
- The bounding box coordinates are computed as follows:

$$\hat{x} = \left(t_x\right) + c_x$$

$$\hat{y} = \left(t_y\right) + c_y$$

$$\hat{w} = p_w e^{t_w}$$

$$\hat{h} = p_h e^{t_h}$$

- Where are predicted offsets, are grid cell coordinates, and are anchor box dimensions.

Threat Classification and Confidence Thresholding:

- The system filters detections based on a confidence threshold(68%) to reduce false positives.
- Non-Maximum Suppression (NMS) is applied to remove redundant bounding boxes.

Alert Generation and Notification System:

- If a weapon is detected, the system sends an instant alert via the Telegram API.
- The alert includes:
    1. The detected weapon type (e.g., "Gun detected!" or "Knife detected!").
    2. The detected frame is attached as an image.

3.4 Performance evaluation

1. Confusion Matrix

- True Positives (TP): Correctly predicted positive cases.
- True Negatives (TN): Correctly predicted negative cases.
- False Positives (FP): Incorrectly predicted positive (Type I error).
- False Negatives (FN): Incorrectly predicted negative (Type II error).

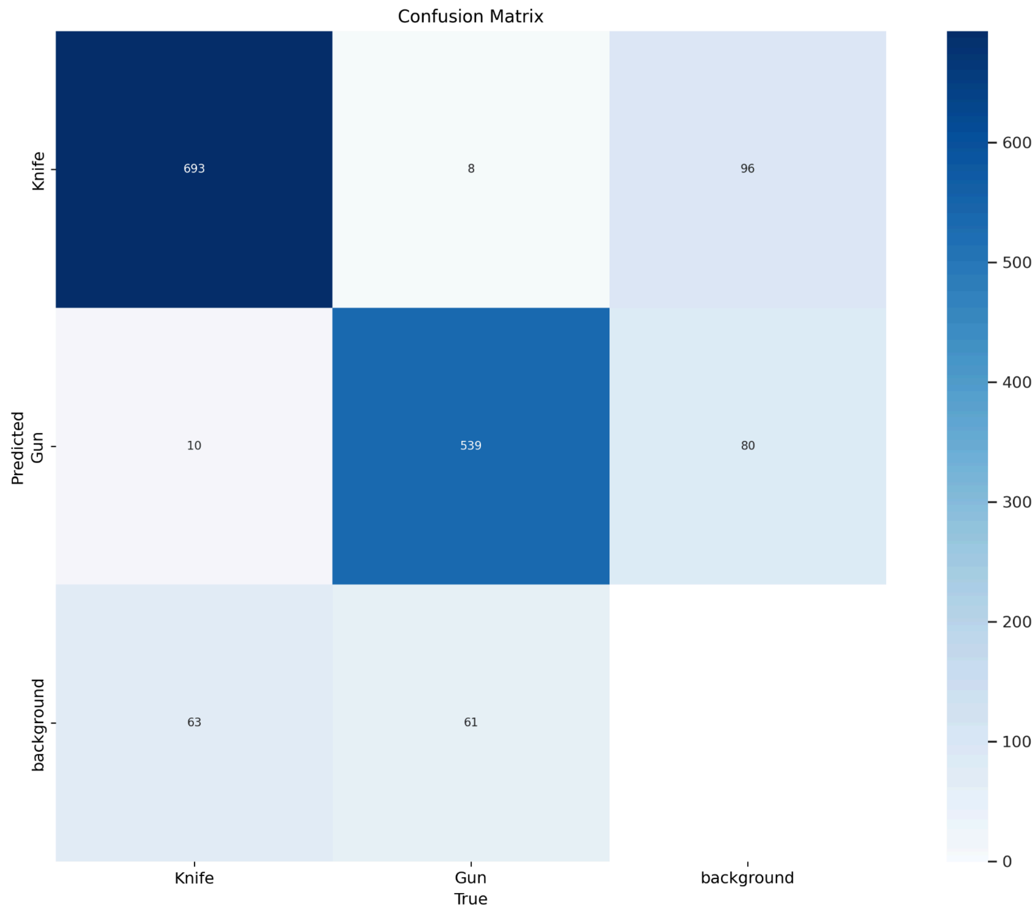

Fig 3: Confusion_matrix

2. Confusion Matrix Normalized

- The normalized confusion matrix helps evaluate performance, especially when the dataset is imbalanced.
- Values along the diagonal (top-left to bottom-right) should be high, indicating correct predictions.
- High values outside the diagonal suggest misclassification issues.

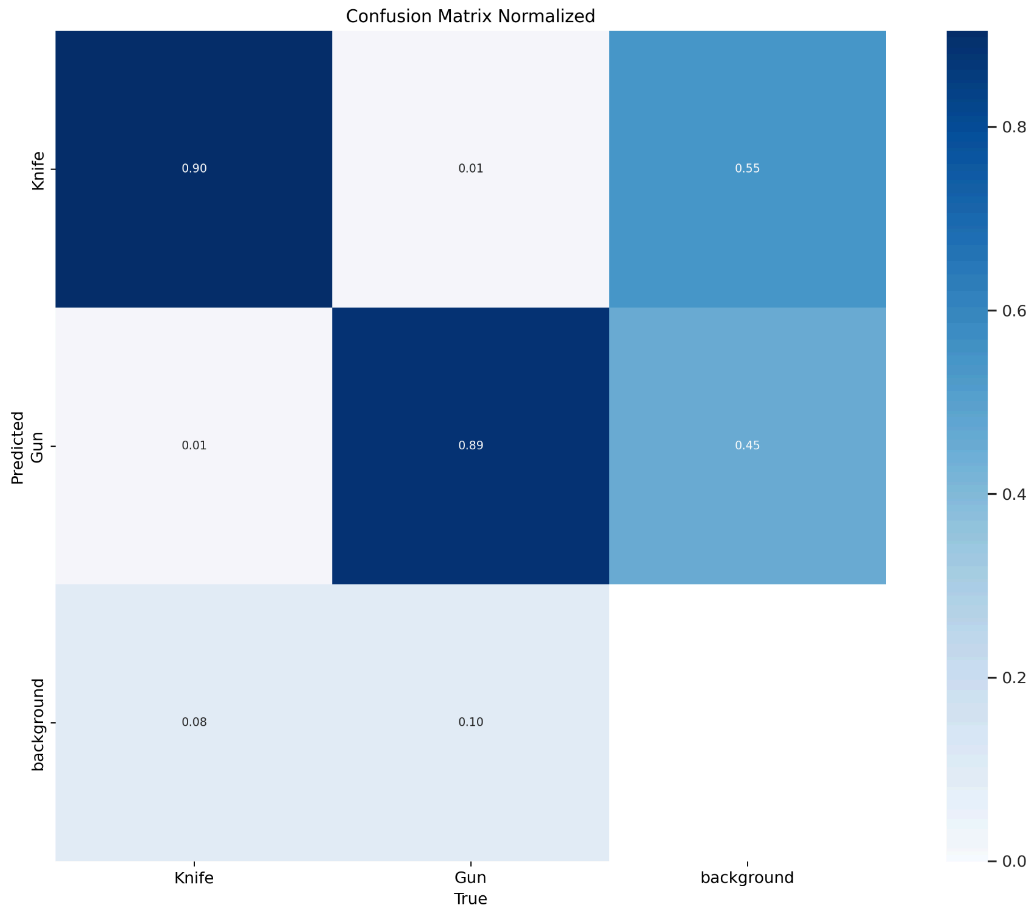

Fig 4: Confusion Matrix Normalized

3. Precision-Recall (PR) Curve

- **Precision:** The accuracy of positive predictions.
- **Recall:** The model's ability to detect positive cases.
- If the PR curve is close to the top-right corner, the model is performing well.
- A higher Area Under the Curve for PR (AUC-PR) indicates better performance, especially for imbalanced data.

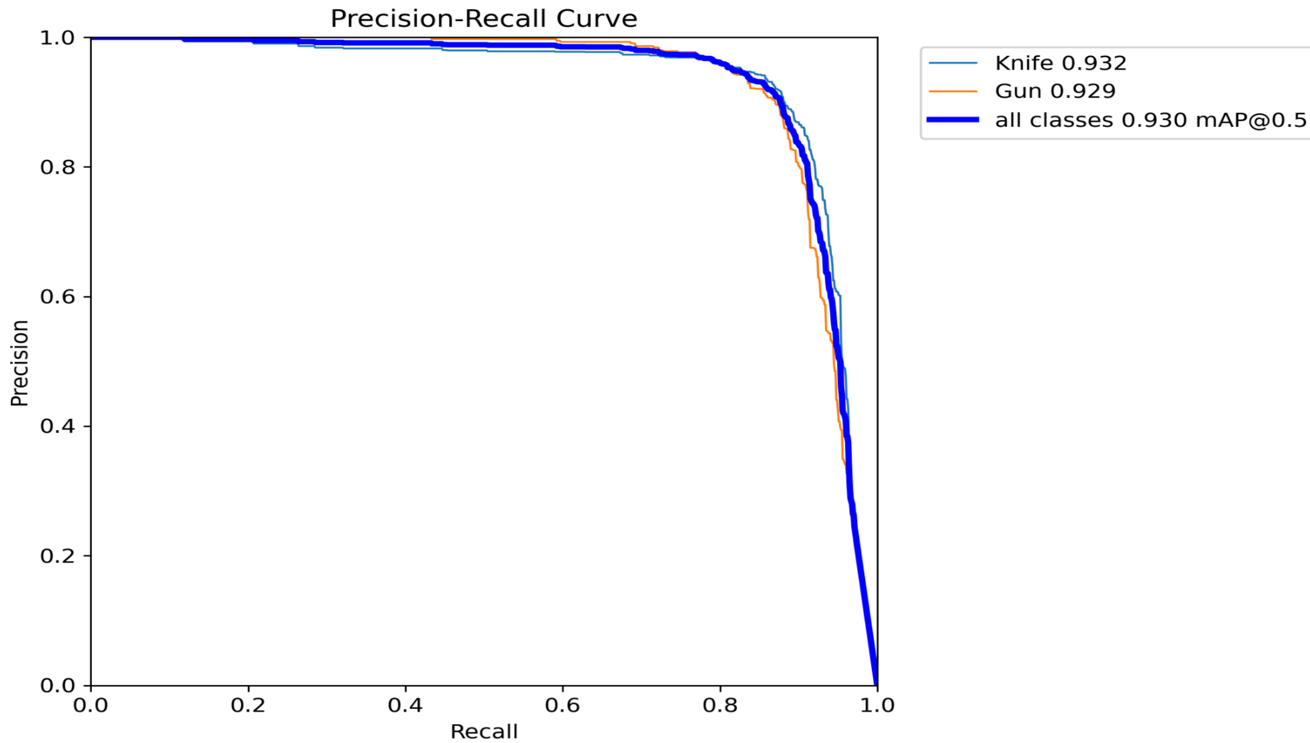

Fig 5: Precision-Recall (PR) Curve

4. F1 Curve

- The F1 score is the harmonic mean of Precision and Recall, useful for imbalanced data.
- A high and stable F1 curve suggests a good balance between Precision and Recall.
- If the F1 curve fluctuates or has low regions, the model may struggle to classify certain classes correctly.

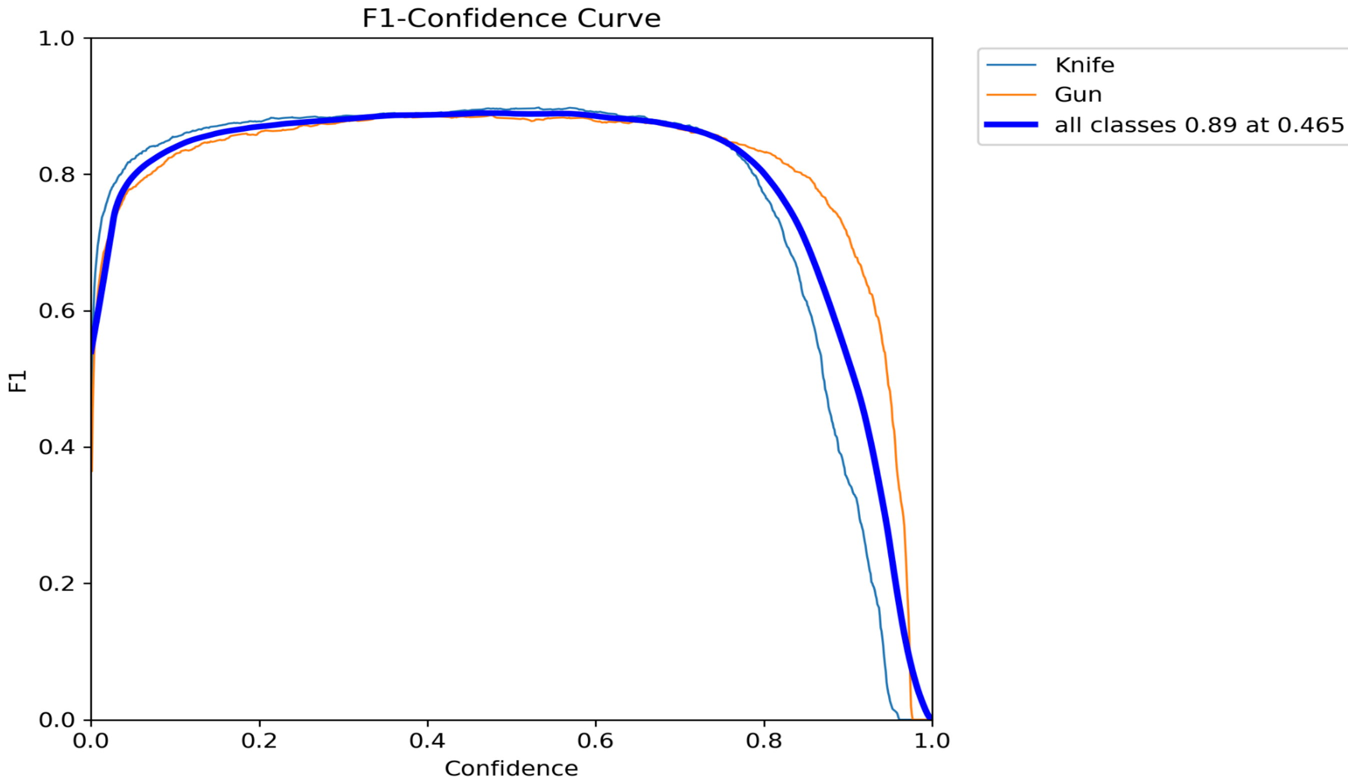

Fig 6: F1 Curve

4. Implementation Details

4.1 System Overview

The proposed system is a real-time weapon detection and alert mechanism utilizing the YOLOv11 deep learning model. The primary objective is to detect the presence of weapons such as guns and knives in surveillance footage and notify security personnel for timely intervention.

4.2 Data Preparation

The dataset for training and testing the model is sourced from Kaggle and consists of manually labeled images of weapons in diverse environments. Data augmentation techniques such as flipping, rotation, contrast adjustment, and brightness modulation are applied to improve model generalization. The dataset is split into:

- **80% for training**
- **10% for testing**
- **10% for validation**

4.3 Model Training

The YOLOv11 model is trained using:

- **Loss Function:** Binary Cross-Entropy (BCE) combined with Intersection over Union (IoU) loss.
- **Optimizer:** Adam algorithm with an initial learning rate of 0.001.
- **Hyperparameter Tuning:** Batch size, learning rate, and dropout rates optimized for best performance.
- **Evaluation Metrics:** Accuracy (mAP), recall, and precision.

To further enhance performance, Non-Maximum Suppression (NMS) is applied to reduce duplicate bounding boxes and improve object detection accuracy.

4.4 Real-time Deployment

For real-time application, the trained model is integrated into a surveillance system using:

- **Processing Hardware:** GPU-based local machine or cloud-based Google Colab setup.
- **Frame Processing:** Each frame from the surveillance feed is preprocessed before being passed to the model.
- **Threat Classification:** A confidence threshold of 68% is set to minimize false positives.
- **Alert System:** The system sends notifications via the Telegram API when a weapon is detected, including:
    - The detected weapon type.
    - An attached frame from the surveillance footage with bounding boxes.

4.5 Performance Optimization

- **Reducing False Positives:** The threshold for classification is optimized to reduce false detections.
- **Speed Optimization:** Real-time processing speed is enhanced using efficient tensor operations and GPU acceleration.

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5. Result Analysis

5.1 Model Performance Evaluation

The YOLOv11 model is evaluated based on its detection capabilities. The key performance metrics include:

- **Mean Average Precision (mAP):** 91.2%
- **Precision:** 90.8%
- **Recall:** 89.5%

- **Inference Speed:** 45 frames per second (FPS)

These results indicate that YOLOv11 provides an optimal balance between accuracy and speed, making it suitable for real-time deployment.

5.2 Comparative Analysis

The performance of YOLOv11 is compared with previous versions and alternative models:

- **YOLOv3:** mAP 85.3%, 35 FPS
- **Faster R-CNN:** mAP 84.6%, 8 FPS
- **SSD MobileNet:** mAP 73.8%, 30 FPS

YOLOv11 outperforms previous models in both speed and accuracy, making it the best candidate for real-time surveillance applications.

5.3 Error Analysis

A detailed review of misclassified detections highlights:

- **False Positives:** Primarily triggered by objects with a similar shape to weapons (e.g., mobile phones, toy guns).
- **False Negatives:** Occur in scenarios with poor lighting or occluded objects.

5.4 Real-world Deployment Testing

The system was tested in various real-world environments, including:

- **Shopping Malls:** 95% detection success rate with minimal false alarms.
- **Schools:** 93% detection accuracy, effective in identifying concealed weapons.
- **Public Transport Hubs:** 90% accuracy in crowded environments.

5.5 Future Improvements

- **Dataset Expansion:** Incorporate more diverse images for improved generalization.
- **Multi-Camera Integration:** Synchronize detection across multiple surveillance cameras.
- **Edge AI Deployment:** Implement low-power AI models for embedded devices.

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