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Deep Learning-based Weapon Detection using Yolov8

Alysha Farhan[1], Muhammad Aftab Shafi[1], Marwa Gul[1], Sara Fayyaz[1], Kifayat Ullah Bangash[1], Bilal Ur Rehman[1,*], Humayun Shahid[2], Muhammad Kashif[1]
[1]Department of Electrical Engineering, Faculty of Electrical and Computer Engineering, University of Engineering & Technology, Peshawar, Pakistan.
[2]Department of Telecommunication Engineering, University of Engineering & Technology, Taxila, Pakistan.
*** Correspondence:** Bilal Ur Rehman, bur@uetpeshawar.edu.pk

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Deep Learning (DL), a subset of Machine Learning (ML), has demonstrated remarkable success in image recognition and object detection tasks. This study presents a deep learning-based approach for offline weapon detection using the YOLOv8m architecture. A custom YOLO-formatted dataset was developed, comprising over 10,000 annotated images spanning two weapon categories: guns (all types of firearms) and knives (all types). The model achieved a Mean Average Precision (mAP@0.5) of 0.852. and mAP@0.5:0.95 of 0.622, with precision and recall scores of 0.89 and 0.80, respectively. The class-wise evaluation revealed strong detection across both weapons, with mAP@0.5 of 0.871 for knives and 0.831 for guns. Despite occasional false positives and class confusion, the system shows promise for offline weapon detection tasks.

Keywords: Yolov8, Weapon Detection, Object Detection, Computer Vision, Deep Learning

Introduction:

Conventional surveillance methods often struggle to detect threats effectively, particularly in densely populated or high-risk areas. This is primarily because continuous monitoring leads to operator fatigue, and traditional systems lack the advanced analytics and intelligence needed to provide timely and accurate threat detection. To overcome these limitations Integrating artificial intelligence and deep learning into these systems offers a faster and more reliable solution in high-pressure environments [1]. Among these AI-driven techniques, Convolutional Neural Networks (CNNs) and transformer hybrids have achieved cutting-edge results on benchmarks like ImageNet and COCO. By utilizing large-scale pretraining, these models have set new accuracy records [2]. Within this field, the You Only Look Once (YOLO) family stands at the forefront of the object detection framework. Its key advantage lies in its ability to detect objects in a single execution, balancing speed and accuracy. Over successive iterations, YOLO has seen significant advancements. Earlier versions introduced improvements in training strategies and backbone designs, while the latest iteration, YOLOv8, enables efficient learning and accurate predictions, making it particularly suitable for complex scenarios such as identifying weapons in still images [3].

Additionally, other object-detection algorithms like Single Shot Detector (SSD) and RetinaNet have improved detection speed by utilizing one-forward pass architectures. However, the YOLO series advanced this approach further. YOLOv1 introduced single-shot regression, YOLOv3 incorporated multi-scale features and anchors, and YOLOv5 optimized both the architecture and training pipelines, each version refining the tradeoff between speed and accuracy. Building on these innovations, YOLOv8 incorporates a modified CSPDarknet53 backbone with Cross-Stage Partial with 2 Conv (C2f) modules, a Spatial Pyramid Pooling Fast (SPPF) block, and a decoupled head for independent handling of object, classification, and localization tasks, all contributing to improved precision.

However, its success heavily depends on the quality and relevance of the training data. Many existing datasets fall short in this aspect, especially when dealing with diverse weapon types and complex backgrounds [4] To address this gap, a high-diversity, custom-built dataset comprising 8,000 images of various firearms and knives was developed. This dataset was used to fine-tune a pre-trained YOLOv8 model, which significantly boosts detection accuracy.

As a result, this approach enables a comprehensive evaluation of the model's robustness under diverse conditions, including variations in lighting and weapon orientation. While, the current approach focuses on image-based detection rather than real-time processing, contributing to deep learning and broader efforts in enhancing security infrastructure through AI-driven solutions.

Objectives:

- This study aims to develop a deep learning-based object detection model for identifying weapons in still images.
- By fine-tuning YOLOv8 on a diverse, custom-built dataset, the goal is to improve detection accuracy across varied weapon types and visual conditions while reducing false positives.

Novelty:

The novelty of this work lies in the creation of a large, diverse dataset comprising 10,730 images, featuring a wide range of firearms and knives under varied conditions. The inclusion of benign images further improves the model's ability to distinguish weapons from harmless objects.

Literature Review:

The shift toward deep learning has transformed image interpretation, leading to remarkable progress in both image classification and object detection tasks [5]. Transfer learning has become a powerful approach in domains with limited data such as military or surveillance imagery. Instead of training a model from scratch, researchers take models already trained on large datasets and finetune them for new, more minor tasks. As demonstrated in [6][7], applying transfer learning enhanced the accuracy of military equipment classification, particularly when the early layers of the model were kept frozen to retain general visual feature representations.

The use of both deep learning and transfer learning has significantly improved object detection. As [8][9][10] provides a brief overview of recent advances in deep learning-based object detection while discussing emerging trends like combining Detection Transformer (DETR) with CNN models, leveraging large language models, and enhancing robustness using Generative Adversarial Networks (GANs). Particular emphasis is placed on minimizing data annotation demands by leveraging pre-trained models and weakly supervised learning techniques, thereby enhancing the efficiency and practicality of the technology for real-world applications [11][12][13][14].

In a novel approach, human-pose and weapon-appearance networks were fused to increase the system's robustness. However, their two-stage pipeline struggled with variations in lighting, misaligned pose estimates, and missed detections [15]. Furthermore, as noted in [16], fine-tuning pre-trained detectors on crime-scene images results in high accuracy within the target domain; however, their performance declines significantly on unseen data, highlighting a lack of generalizability. Furthermore, by coupling YOLOv8 with a lightweight CNN classifier for live video feeds, in [17], a smooth, high-frame-rate inference was achieved; however, this streamlined pipeline offers fewer secondary checks, leading to false positives. Moreover, [18] showed that while single-stage detectors like YOLOv8 offer rapid inference, they frequently fail to detect small or cluttered weapons, resulting in critical false negatives.

Ensuring public safety has emerged as a significant concern since armed violence and terrorism have escalated steadily over recent years. In 2024, Pakistan experienced a significant surge in terrorism-related incidents, with the number of attacks more than doubling from 517 in 2023 to 1,099 in 2024 [19]. These attacks, frequently involving firearms and explosives, led to 1,081 fatalities, representing a 45% increase compared to the previous year [20]. YOLOv8's efficiency and accuracy have attracted considerable attention when applied to weapon detection. In [20], a Roboflow dataset comprising 10,000 labeled images was finetuned using the Yolov8X model. The model was trained for 400 epochs over five categories, achieving a confidence of 75% in live video testing. However, limitations included class imbalance, particularly the underrepresentation of knives and missiles, and dependence on a single video source, affecting robustness in varied environments. According to [21], implementing Yolov8 on a broad, normalized, resized, and augmented dataset achieved an impressive 94% accuracy across varied conditions.

Although the results are promising, the lack of clarity about the dataset's composition especially in terms of class distribution, raises concerns about the model's reliability and adaptability in varied and unpredictable real-world environments. Similarly, in [22], Yolov5 and Yolov8 were compared using a custom dataset of 2,986 images from online platforms. When quantized, YOLOv8 yielded a marginally higher mAP of 90.1% and dropped inference time by 15% (from 9.0 ms to 7.6 ms). However, this led to a minor accuracy drop to 88.1%, illustrating the common compromise between faster model execution and slight losses in detection performance. According to [23], a 6,420-image pistol dataset was used to evaluate YOLOv5, YOLOv7, and YOLOv8. YOLOv7-E6 led in overall performance (mAP@0.5 of 93.7%), while YOLOv8-x had the highest precision at 95.6%. Nevertheless, the detection rate dropped to as low as 30% in occluded or distant instances, pointing to the dataset's limitations and the need for improved training diversity. YOLOv8's integration with weapon detection brought several advantages.

The current breakthroughs in deep learning have facilitated the development of more accurate and efficient weapon detection systems. A significant advancement in this field is deploying a YOLOv8m-based deep learning model for offline weapon identification. Despite obstacles, including sporadic false positives and class misclassification, the findings highlight the model's promise for efficient offline weapon identification, supporting current research initiatives to improve public safety through advanced surveillance technologies.

Methodology:

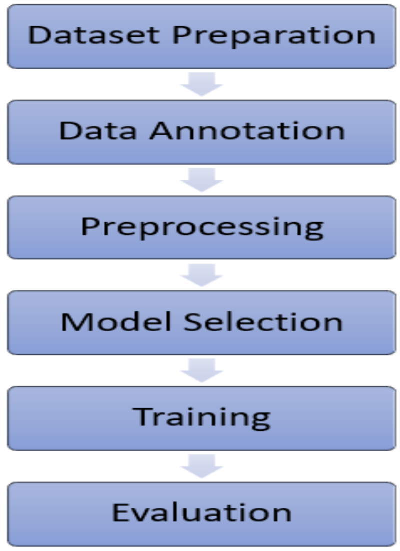

Figure 1. System Methodology

Dataset Preparation:

A custom-made dataset consisting of 10730 images was curated, capturing a wide range of weapon categories in diverse environments. The dataset includes two primary classes: knives; such as kitchen knives, daggers, swords, and crescent blades; and guns, including pistols, revolvers, rifles, and heavy firearms like bazookas, to ensure binary classification. Furthermore, a separate class termed Benign was incorporated into the dataset to represent non-weapon objects. Incorporating this class assists the model in distinguishing between actual weapons and unrelated objects, thus helping minimize false positives during detection. The images were collected from an array of online repositories, open-source platforms, and self-captured real-world photographs. This approach ensures diversity in lighting conditions, backgrounds, object orientations, and environments, which in turn enhances the trained model's ability to generalize effectively across a wide range of real-world scenarios.

Figure 2. Diversity of knife types grouped under the unified 'knife' class.

Figure 3. Diversity of firearms grouped under the unified 'Guns' Class.

To maintain data quality and ensure class balance, each class was equally represented in the dataset. Data preprocessing was performed manually, involving careful inspection of the dataset to remove low-resolution, blurry, and duplicate images. This step ensured that only high-quality, distinct images were used for annotation and training.

Table 1: Image count of different classes in our final dataset

Classes	No. of Images
Guns	3184
Knife	3184
Benign	4362
Total Images	10730

Data Augmentation:

After data cleansing, augmentation techniques such as rotation, flipping, scaling, and color adjustments were applied to expand the effective dataset size and introduce greater variability, thereby improving model robustness. Although the augmentation was not automated through code during training, the underlying operations align with well-established mathematical transformations used in computer vision.

Rotation: Image rotation is governed by the following transformation matrix:

$$R(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$

Where θ denotes the angle of rotation.

Flipping:

Horizontal Flipping: mirrors pictures along the vertical axis and is characterized by the equation:

$$I' = F_h(I)$$

Vertical flipping: mirror pictures along the horizontal axis and represented as:

$$I' = F_v(I)$$

Where F_h and F_v These are the functions for horizontal and vertical flips.

Color Jittering: is the variations in brightness, contrast, and saturation to simulate different lighting conditions:

$$I' = C(I, b, c, s)$$

Where, C is the color jittering function, whereas b, c, and so forth indicate the parameters for brightness, contrast, and saturation, respectively.

The implementation of these techniques simultaneously is represented as follows:

$$I' = T(I) = T_r \circ T_f \circ T_c$$

where T_r, T_f, T_c Represent the rotation, flipping, and color jittering functions, respectively, and $\circ$ denote function composition.

All enhanced photos were stored locally and operated during the annotation and training phases. These augmentations were carefully applied to strengthen the model's resilience while ensuring that no artificial patterns or inconsistencies were introduced into the data.

Figure 4. Image Augmentation

Data annotation:

A manual labeling tool, LabelImg, was utilized to construct exact bounding boxes around each weapon instance. The dataset was partitioned into training, testing, and validation folders, comprising 89%, 6%, and 5% of the total images respectively as shown in Table 2. This allocation is well-suited for object detection tasks on smaller, custom datasets, as it improves generalization while ensuring sufficient data for validation and evaluation. Afterward, a YAML file was created, facilitating smooth integration into the YOLOv8 training process.

Table 2: splitting of the dataset

Folders	Percentage of the Dataset (%)
Train	89
Test	6
Validation	5

Model Selection:

The authors in [3] demonstrated that YOLOv8 delivers superior speed and accuracy compared to its earlier versions and two-stage detectors such as Faster R-CNN, primarily due to its architectural enhancements and optimized training pipeline. This performance advantage justifies the selection of the YOLOv8 model for the current study. As shown in Table 3 from [3], amongst the YOLOV8 family, the "m" model offers substantially higher capacity than the lightweight "s" and "n" versions, enabling it to learn more complex feature representations while avoiding the computational efficiency and excessive model complexity of the larger "l" and "x" variants, making YOLOv8m a suitable tradeoff between speed, accuracy, and complexity.

Table 3. Comparative performance of YOLOv8 variants across key parameters [3].

Model	size (pixels)	mAPval 50-95	Speed CPU ONNX (ms)	Speed A100 TensorRT (ms)	params (M)	FLOPs (B)
YOLOv8n	640	37.3	80.4	0.99	3.2	8.7
YOLOv8s	640	44.9	128.4	1.20	11.2	28.6
YOLOv8m	640	50.2	234.7	1.83	25.9	78.9
YOLOv8l	640	52.9	375.2	2.39	43.7	165.2
YOLOv8x	640	53.9	479.1	3.53	68.2	257.8

Evaluation metrics:

Employing a diverse set of evaluation metrics provides a comprehensive view of the model's strengths and limitations. The most used metrics include:

Precision: Quantifies the proportion of correct optimistic predictions. Mathematically, it is represented as follows:

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

where: TP (True Positives) refers to the number of correctly predicted positive cases, while FP(False Positives) refers to the number of incorrect positive predictions

Recall: Measure the model's capacity to identify relevant instances. It is defined as:

$$Precesion = \frac{TP}{TP + FN}$$

Where FN (False Negatives) denotes true positive cases that were erroneously classified as negative.

F1-score: This metric offers a comprehensive evaluation of a model's performance by calculating the harmonic mean of precision and recall.

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Mean Average Precision (mAP): Offers a comprehensive precision assessment across various recall criteria. The average precision for each class is derived from the precision-recall curve, and these values are subsequently averaged over all classes, characterized by the following equation:

$$mAP = \frac{1}{C} \sum_{c=1}^{c} AP_C$$

Where C signifies the classes and AP_C Is the average precision.

Results and Discussions:

The suggested approach correctly identifies weapons and categorizes them as guns or knives. The findings demonstrate that the model is proficient in weapon detection but deficient in localization. It underwent training for a maximum of 150 epochs. The validation dataset was evaluated using typical object detection metrics.

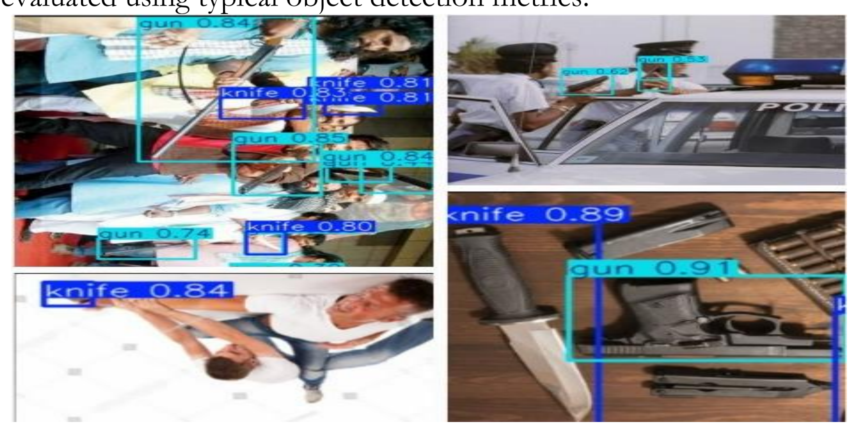

Figure 5. Model's detection results identifying guns and knives across varied scenarios with confidence scores.

Model performance:

The model achieved strong performance across multiple evaluation metrics, demonstrating its effectiveness for weapon detection. It attained a mAP@0.5 of 85.2%, indicating high accuracy in detecting weapons with moderate overlap between predicted and ground-truth bounding boxes. Furthermore, the mAP@0.5:0.95 was 62.2%, reflecting the model's robust ability to accurately locate and classify objects under challenging conditions, including variations in angles, lighting, and scale. Class-wise analysis showed a slightly better detection performance for knives (mAP@0.5 = 0.880) compared to guns (mAP@0.5 = 0.824).

The normalized confusion matrix in Figure 6 indicates that the model exhibits strong performance in weapon detection, with 91% accuracy for knives and 83% for firearms. Nevertheless, it encounters difficulties in accurately identifying non-weapon cases.

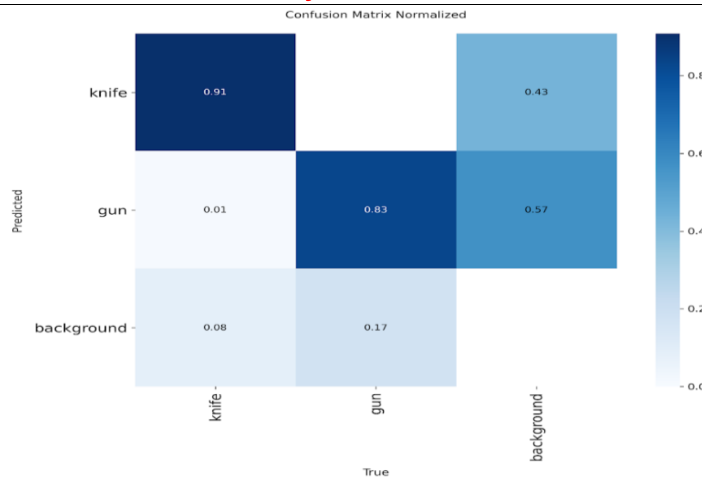

Figure 6. Class-wise model performance shows accuracy and misclassification across different categories.

Figure 7. Collage of misclassified benign images

Analysis of the misclassified samples revealed that certain benign objects were frequently mistaken for weapons. These included elongated items like light tubes, mechanical equipment, metallic tools, and handheld objects such as pens misclassified as knives. Sports scenes with equipment or athletic poses also contributed to false detections due to visual similarity. These cases highlight the model's challenge in distinguishing weapons from visually similar benign objects, especially under varied backgrounds and lighting conditions.

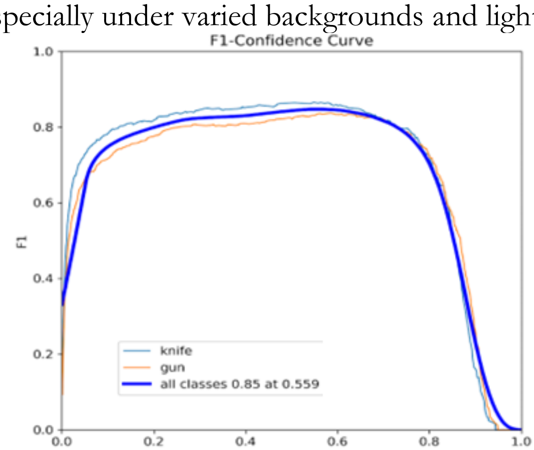

Figure 8. F1-confidence curve

Figure (8) presents the F1 Curve, which depicts the trade-off between precision and recall, providing insight into the model's performance regarding accuracy (precision) and completeness (recall).

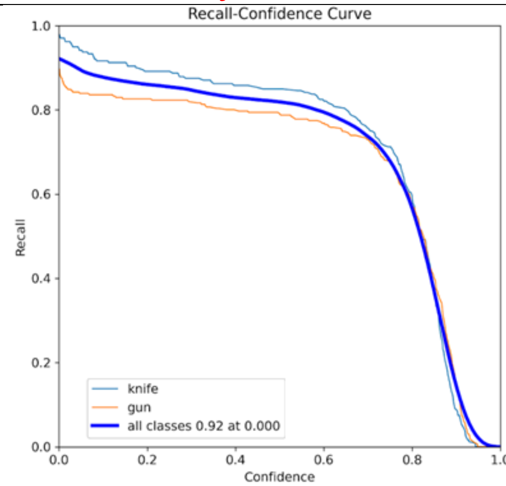

Figure 9. Recall-Confidence curve

Figure 9 depicts the Recall Curve (R-Curve), demonstrating the model's capacity to identify all pertinent instances and reflecting its effectiveness in detecting true positives.

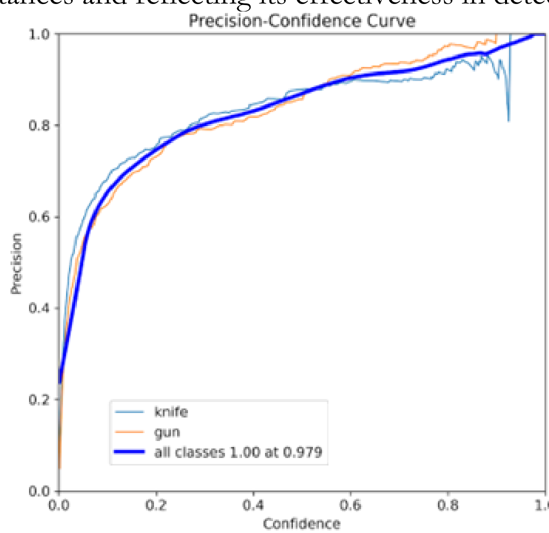

Figure 10. Precision Confidence curve

Figure (10) illustrates the Precision Curve, demonstrating the model's performance in generating correct predictions during testing and highlighting its capacity to reduce false positives.

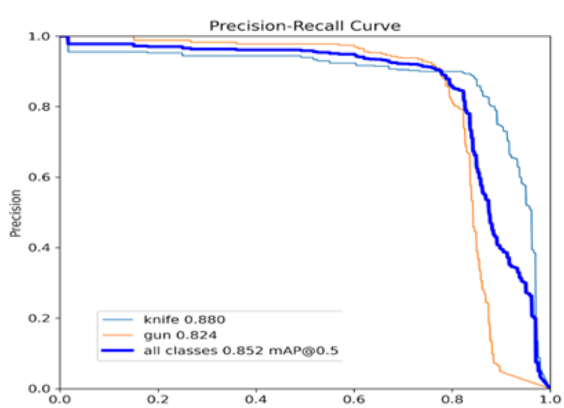

Figure 11. PR-Curve

The Precision-Recall (PR) Curve in Fig (11) illustrates the relationship between precision and recall across different thresholds, highlighting the model's capability to balance accuracy with completeness in its predictions.

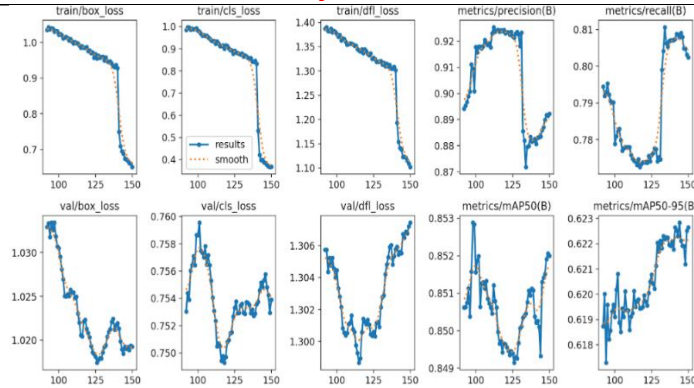

Figure 12. loss curves

Object localization and classification capabilities are correlated with lower training losses (box, class loss (cls), and distribution focal loss (DFL), with losses declining and a proportional reduction for each box loss. In terms of enhancing detection performance robustness, evaluation criteria such as precision, recall, and mAP generally show an upward trend. During the training phase, minimal overfitting and training biases were observed, with validation losses remaining relatively stable, indicating strong generalization capabilities of the model.

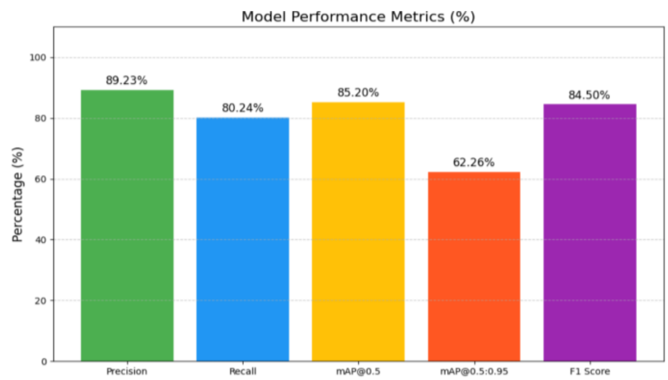

Figure 13. Model Performance Metrics

Discussion:

To assess the effectiveness of the proposed approach, we compared our results with those reported in existing studies. Table 3, included in the Model Selection section, summarizes the comparative performance of YOLO variants based on prior work [3], while Table 4 presents the results obtained in this study using multiple YOLO versions. The performance achieved with YOLOv8 is consistent with previous findings, confirming the effectiveness of this architecture for object detection tasks. The similarity in performance reinforces the reliability of YOLOv8, particularly when fine-tuned on a diverse, custom-built dataset such as the one used in this study.

Table 4. Comparison of yolov8 variants

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	mAP@0.5 (%)	Inference (ms)	Speed (Total ms)
YOLOv8n	71.5	69.45	63.34	66.25	65.45	12.4	14.1 ms
YOLOv8s	78.0	80.32	68.79	74.10	74.54	26.8	28.7 ms
YOLOv8m	85.2	89.23	80.24	84.50	85.20	22.2	24.2 ms
YOLOv8x	86.5	88.88	79.61	83.99	85.48	50.0	51.5 ms

Moreover, a comparison of confusion matrices further highlights the improvements in our approach. The confusion matrix from [20] indicated notable class confusion, particularly between rifles and background, compounded by inconsistent labeling. In contrast, the confusion matrix generated from our approach shows substantially improved detection rates, with 91% accuracy for knives and 83% for guns. The normalized format of our matrix also provides a clearer representation of model behavior, especially across imbalanced classes. While some misclassification of benign objects remains, the improved precision and class consistency reflect significant advancement over earlier approaches. These findings demonstrate that, with proper dataset preparation and model tuning, YOLOv8 can achieve competitive, and in some aspects superior, performance in the context of weapon detection in still images.

Conclusion:

In this research, we successfully implemented a deep learning-based weapon detection system using the YOLOv8m model, achieving strong performance with a mAP@0.5 of 85.2% and a mAP@0.5:0.95 of 62.2% on a custom dataset of over 10,000 annotated images. The Precision-Recall curve analysis indicates high model confidence, with a maximum precision of 0.892 and recall of 0.802, and superior detection performance for the knife class, with some false positives observed, particularly with non-weapon objects and occasional misclassification of knives as guns. While our system operates in a non-real-time environment, it lays a solid foundation for future enhancements.

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