Integration of Object Detection in Crime Scene Investigation

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Abstract. *Object detection is applicable in various fields, encompassing Crime Scene Investigation. The act of capturing evidence through photography in crime scenes is of paramount importance. Concurrently, object detection and scene analysis can be integrated by the investigator during this process. Nonetheless, the investigative procedure involves multiple phases. In this research, object detection is employed to identify crucial evidence discovered at crime scenes, along with objects commonly linked to assault cases as statistics reported by the National Institute of Justice (NIJ) in the United States of America. Challenges such as pen guns and illegal firearms persist in criminal activities, although they are not no category of legal firearms. Transfer learning techniques are adopted in this study from an existing model, utilizing pre-trained models to identify crucial evidence in crime scenes. The experiment gathered 494 images of pen guns, illegal firearms, and associated objects from online police news reports to form a custom dataset. The process of annotating, training, evaluating, and fine-tuning the custom dataset led to experimental outcomes demonstrating a high Mean Average Precision (mAP) across all target's custom datasets. The model reached convergence at approximately epoch 100, achieving high precision as 0.97, recall as 0.926 and box mAP50 of as 0.974 Additionally, box mAP50-95 as 0.817 However, this paper presents a confusion matrix of customized specific classes with a low volume dataset. These findings highlight the potential application of object detection in crime scene investigations with the aid of object detection. Consequently, this approach could aid in formulating a project blueprint for a Crime Scene Investigation model and furthering the detection of evidence objects in the future with very large volume of dataset. In conclusion, this study illustrates the capability of detecting pen guns, illegal firearms, and related objects through object detection techniques.*

Keywords:

YOLOv8, Object Detection, Crime Scene Investigation, Forensic Science, Custom Dataset

1. Introduction

When a crime occurs, it is imperative for the investigator to engage in a comprehensive and meticulous scrutiny of the scene where the criminal act took place. Such an investigative process involves a meticulous and systematic gathering of tangible evidence with the aim of establishing crucial information that could shed light on the circumstances surrounding the crime. This multifaceted procedure comprises a wide array of meticulous examinations and intricate analyses that are essential for piecing together the different elements of the crime[1]. The utilization of photography plays a pivotal role in the realm of legal proceedings as it serves the purpose of vividly illustrating the narratives pertaining to the crime, rather than delving into the minutiae of detailed investigations [2][3]. The art of capturing images of crime scenes is significantly influenced by a myriad of factors such as social class distinctions, racial dynamics, and gender perspectives that shape the overall narrative of the crime[4]. Furthermore, it has been observed that the efficacy of utilizing photography in legal settings is more pronounced when these visual representations are presented in a formal courtroom environment [5]. However, this paper does not include the crime scene reconstruction technique but aims to use object detection to utilize object detection to assist in Crime Scene Investigation (CSI).

Importantly, the evidence discovered at crime scenes often differs from everyday objects. For instance, a knife may display various bloodstains that are challenging for computer vision to discern. The proper procedure for photography is to capture images prior to collecting evidence. The process of photographic documentation plays an essential role in the thorough portrayal of the environment and the establishment of a strong correlation between the various pieces of evidence gathered at the scene. This meticulous process involves the systematic capturing of visual content not only prior to but also after the thorough examination of the crime scene. In the final analysis, it becomes imperative for the investigator to methodically present this comprehensive photographic documentation as a key piece of evidence in the court of law. The current research delves into the utilization of an advanced artificial intelligence framework that is specifically designed with sophisticated object detection capabilities aimed at precisely recognizing crucial pieces of evidence and adeptly capturing detailed images of evidence throughout the investigative process of crime scenes.

The advantages associated with object detection encompass various aspects such as enhancing the safety of law enforcement officers by reducing their exposure to potential dangers, aiding investigators in their tasks, preventing the contamination of crucial evidence, and facilitating the analysis of pertinent evidence. An illustration of this can be seen when the system provides guidance to the officer on locating a shell casing upon detecting a firearm at a crime scene, which could potentially contain valuable evidence or present risks. There are instances where investigators may encounter situations where criminals intentionally place dangerous items near the crime scene to mislead or cause harm to law enforcement personnel. Moreover, the use of photography plays a significant role in documenting evidence that will be presented in court proceedings.

However, the focus of the analysis will be limited to specific aspects of the evidence imagery within this study. Hence, the incorporation of advanced deep learning methodologies is crucial for the accurate identification of objects as forensic evidence, with potential applications of transfer learning techniques to improve the capabilities of CSI models in the future. Within the context of this research endeavor, object detection aims to identify unusual items such as pen guns, illicit firearms, and related objects that hold significance in forensic investigations.

2. Background

Object detection has demonstrated its versatility by using applications across diverse fields, such as crime scene investigation in forensic investigation[6], [7]. It utilizes the Faster R-CNN algorithm in this context. Weapon detection in smart surveillance system[7]. It significantly enhances object detection accuracy on multiple datasets[8]. Moreover, a comprehensive survey conducts to gain valuable insights into various object detection techniques and their wide-ranging applications[9]. These surveys explore the challenges, opportunities, and future research directions, including the intriguing area of crime prediction[10] or automatic classify crime scene[11]. Crime scene investigation involves identifying general objects and specific items that may appear unusual compared to everyday objects, such as biological evidence, tool marks, and traces. Many systems have focused on using deep learning CNN-based approaches for detecting and analyzing evidence in crime scene images related to crime[12]. Consequently, it depends on the technique and limitations of tools and methods specific to the evidence type. For example, surveillance systems use YOLOv3 to detect and classify guns[7]. Some work evaluates datasets containing images of firearms [13],[14],[15]. However, the experiment aims to advance object detection techniques in forensic science, specifically in crime scene investigation. This section leads to basic forensic science and how object detection can be applied.

A. Evidence and Crime Scene Investigation

Evidence refers to information, facts, or data that supports or contradicts claims, assumptions, or beliefs. Evidence is pieces through experiments, observations, analysis, and rigorous research methods in scientific research. It serves to validate theories and confirm their validity. In a legal context, evidence supports or challenges specific assumptions and may be presented in court to prove or disprove a defendant's guilt[16]. In forensic science, evidence encompasses diverse types of physical[16], biological[17] trace [18], and digital evidence[19], subjected to multiple analysis techniques to support investigations. These objects may include weapons used in the crime, bloodstains, and changes observed in both the perpetrator and the victim, such as the condition of clothing and items related to the criminal case. Fortunately, The National Institute of Justice (NIJ) United States of America provides statistical data reports on crime evidence [20]. So, we analogy as the same incident of crime and use this report to reference assault cases at the crime scene and related types of weapons object detection (aka physical evidence).

Table 1 Evidence categories of NIJ assault case

Evidence type	Example
Biological	Bloodstain etc.
Latent Prints	Fingerprint on object surface etc.
Pattern Evidence	Tools/marks etc.
Guns/Weapons	Guns/Weapons[a] etc.
Natural/Synthetic Materials	Clothing etc.

[a.] Pen guns, illegal firearms and related objects are instance of physical evidence type Guns/Weapons.

B. Traditional Object Detection

Traditional object detection techniques use simple feature extraction and machine learning algorithms. Popular methods include 1) The Viola-Jones algorithm, which uses the properties of haarcascade, and the AdaBoost classifier to detect objects as a fast and efficient algorithm but less accurate than modern methods[21]. 2) HOG (Histogram of Oriented Gradients) extracts features based on the slope values of the image. It is fast and efficient, but there are problems with complex textures and shapes objects [22]. 3) SIFT (Scale-Invariant Feature Transform), which extracts various characteristics based on scale, rotation, and brightness changes, is more effective for image variations. However, it requires high computational power[23]. As traditional methods are widely used, advancements in deep learning have introduced new techniques for object detection. For example, face detection performs haarcascades, but deep learning-based classification methods can be employed instead of the traditional method.

C. Artificial Intelligence and Object Detection

Deep learning-based object detection is widespread due to its ability to handle large datasets with extensive annotations and the availability of powerful GPUs for training. Among the various deep learning techniques, 1) Region-based Convolutional Neural Networks (R-CNN) is a hybrid of region and convolutional neural networks in object detection [24]. 2) You Only Look Once (YOLO) is known for its speed and efficiency. It is reasonable for real-time applications requiring quick responses[25]. 3) A Single Shot Detector (SSD) uses a series of convolutional layers to capture features at multiple scales, enabling the detection of objects of various sizes[26]. The YOLOv8 model is utilized in this research for the purpose of target identification. Following the utilization of the YOLOv8 model, an in-depth elucidation of the architectural background is elaborated in brief within Fig. 1. [27]

categorizing objects. It employs a uniform systolic array structure with a coordinated pipeline adder tree for convolution, thus ensuring scalability across various levels of precision. In Fig.1 YOLOv8's framework integrates path-planning algorithms to optimize architectural layouts, thereby enhancing user experience and environmental considerations. Furthermore, the architectural design of YOLOv8 draws upon the principles of traditional concise architecture, incorporating elements such as spatial arrangements, environmental adaptability, and communal utility into contemporary architectural frameworks[27].

However, YOLOv8 is an easy machine-learning API to learn and utilize in CSI domain. It suits pen guns, illegal firearms, and related physical evidence. It has several advantages over other machine learning libraries. It is faster and more flexible and provides optimizations that make it easier to train models. YOLOv8 can be an API or library

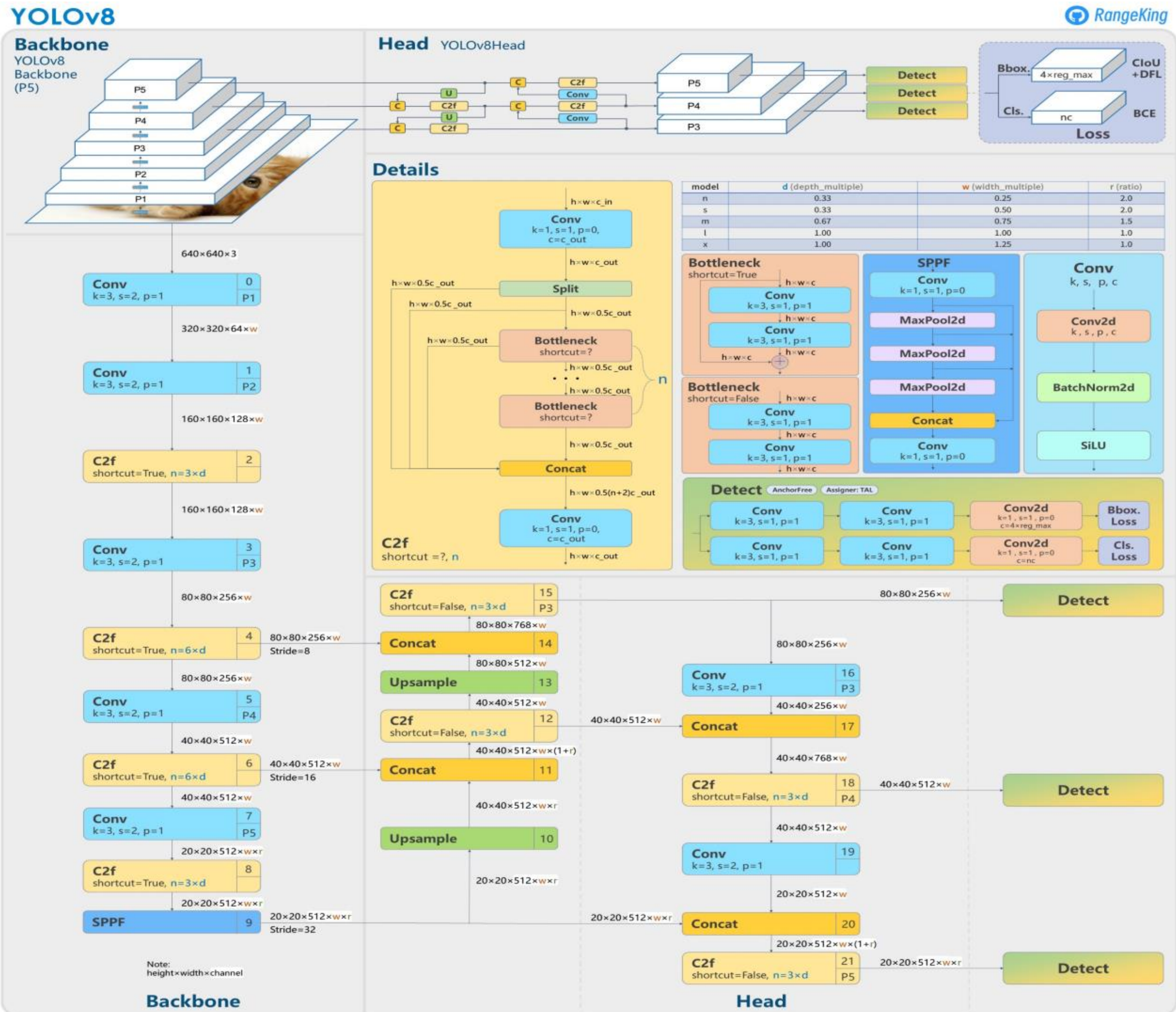


Fig. 1 YOLOv8 Architecture [27]

The YOLOv8 architecture represents a notable progression in object detection technology. It is based on advanced deep learning neural networks, YOLOv8 exhibits outstanding efficiency and precision in identifying and

with programming code and a command line[28]. We can see core architecture of YOLOv8 in Fig. 1

3. Materials and Methods

Illegal firearms are frequently used in fatal crimes worldwide, making it challenging to investigate their sources. A crucial aspect of the experiment involves acquiring images from free of charge online images and crime scene evidence. To initial the project, the authors categorized different types of evidence based on assault case reports from the United States Department of Justice [20]. We selected physical evidence categories and specified pen guns, illegal firearms, and related objects. Then, do a pre-trained supplementary model, "yolov8n.pt" by transfer learning. The model supplements with an additional dataset annotated in the COCO format. However, the research selects high-frequency and prominent evidence types for object detection, as outlined in Table 1.

This experiment aims to detect pen guns, illegal firearms, and related objects using the YOLOv8 algorithm by training a custom dataset. After that, create an illegal firearms model and associated objects, evaluate its performance using this validation dataset, and find the possibilities to extend this work to crime scene investigations in the future.

Since preparing dataset encompassing all real-world objects for deep learning is impractical, the focus is placed on objects and evidence frequently encountered in crime scenes that may be limited. However, the experiment follows the framework, and the preparation steps in a computer vision technique for object detection are in Fig.2

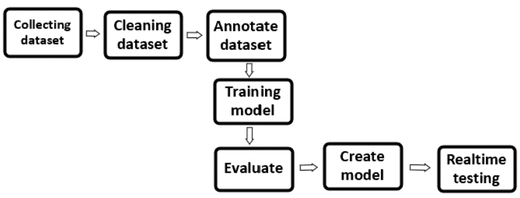


Fig. 3 Object detection framework samples dataset

A. Dataset

Fig. 3 shows samples of pen guns, which are hidden firearms disguised as writing instruments, along with illegal firearms, which are unlawfully held weapons, and different datasets that were utilized in training the model, obtained through the careful selection of pertinent images closely connected to the topic. Pen guns, illegal firearms, and other associated objects are categorized into a total of 7 distinct classes, each representing a different type or category within this domain of study.

[*'PenGun', 'ImitationShotGun', 'ShotGunBullet', 'Bullets', ' Bullet', 'ImitationRevolverGun', 'ImitationRifle'*]

The experimental procedure involved the retrieval of various objects such as pen guns, illegal firearms, and related images from a total of 494 samples, which amounted to a size of 32.4 MB specifically for the annotated objects. It is crucial to underscore that a single image in the dataset can involve multiple instances of the objects of interest. For an example in a visual format, please see Fig. 3 showing a sample object during the annotation

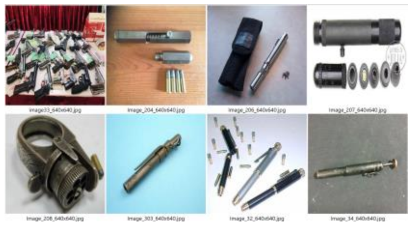


Fig. 2 Samples of Pen guns, illegal firearms, and related objects samples dataset

phase. Pen guns, illegal firearms and related objects are defined in COCO format. The study creates directories of trains, tests, and validates dataset and puts them all annotated images to each directory. Finally, create "data.yaml" points to source of dataset for training step.

Fig. 4 Example of custom dataset annotation

Fig. 4 is a sample of illegal firearms in COCO format. After annotating the image, we find labels and the class identification type in the annotated image text file. We follow ultralytics documentation using command lines on the custom dataset.

The identification of the learning system's scope and the creation of a learning model are clearly delineated and expounded in Fig. 2, offering a comprehensive overview of the process. Commencing the experimental procedures, the initial phase involves the meticulous collection of a diverse dataset encompassing illegal firearms and associated items sourced from online platforms at no cost, as depicted samples in Fig. 3. A pivotal aspect of this stage includes the utilize of a support function tailored for the purpose of data retrieval; however, certain elements within the dataset may lack relevance to the primary objectives that the system need to be focus on object detection. Subsequently, the subsequent phase necessitates a thorough data cleansing process and the implementation of specific criteria for the selection of target objects, ensuring a refined and precise dataset for further analysis and model development.

B. Detection Algorithm

The inclusion of enhancements such as spatial attention mechanisms, feature fusion techniques, and context aggregation modules has enabled the YOLOv8 algorithm to outperform its previous versions. These significant modifications have led to notable advancements in terms of both speed and precision, ultimately establishing YOLOv8 as a prominent player among the various object detection algorithms currently utilized within the field of crime scene investigation. However, detection algorithms under YOLOv8 concept with Intersection Over Union (IoU) are employed for determining the correct prediction of the bounding box. It indicates how much bounding boxes overlap[29].

$$IoU = \frac{area(B_p \cap B_{gt})}{area(B_p \cup B_{gt})} \tag{1}$$

where:

- B_{gt} *is ground truth bounding box*
- B_p *a predicted bounding box*

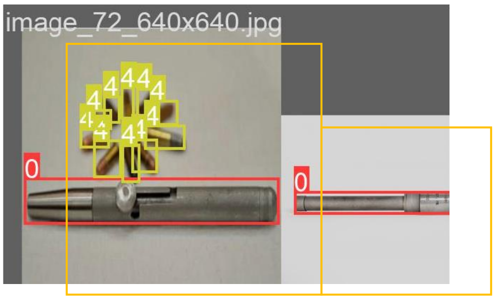


Fig. 5 sample of IOU in training phase

In Fig. 5 of training phase, the Intersection over Union (IoU) metric in the YOLOv8 model is utilized to distinguish and delineate the spatial overlap between the ground truth bounding box and the predicted bounding box. This analysis aims to precisely determine the classification of the objects within the target dataset base on IoU threshold 0.5 in this experiment.

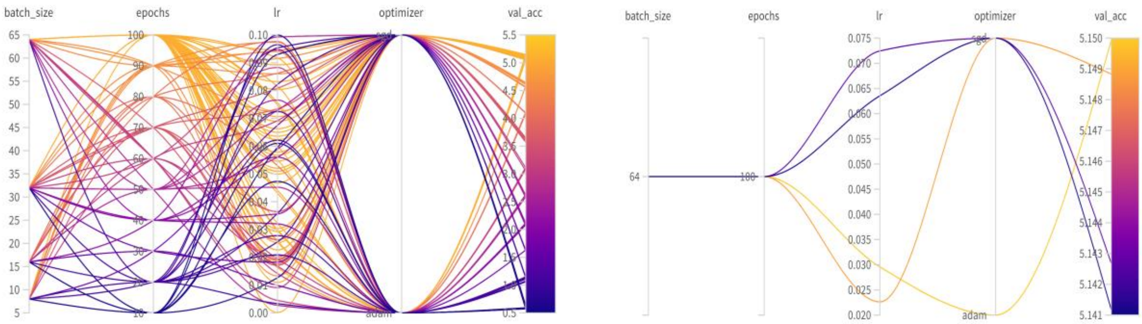
YOLOv8 made a transition to anchor-free detection methodology with the goal of enhancing generalization capabilities. The rationale behind this shift lies in the limitations of anchor-based detection systems, where the utilization of predefined anchor boxes tends to impede the learning process, especially when dealing with customized datasets. In contrast, the anchor-free detection approach enables the model to directly estimate an object's mid-point, thereby reducing the necessity for many bounding box predictions. This adjustment in methodology plays a crucial role in speeding up Non-max Suppression (NMS), which serves as a pivotal pre-processing step focused on eliminating inaccurate predictions[30].

After IoU distinguish and delineate the spatial overlap between the ground truth bounding box and the predicted bounding box. The next step, the algorithm trying to predict and classify target objects depends on IoU accuracy distinguishing. Example in Fig.6 validation dataset with labeling and predictions confidence value of pengun.

Fig. 7 Results of hyperparameter optimization

C. Hyperparameter optimization and training process

Parameter optimization was performed to elevate the effectiveness of the upgraded YOLOv8 model in the ongoing investigation. The optimization of hyperparameters was carried out through the utilization of the weight and bias technique, considering factors such as image dimensions and batch size. In Fig. 7, specifically the image dimensions were set at 640, while the batch sizes varied from 8, 16, 32 to 64. Nevertheless, this initial trial involved the utilization of yolov8n.pt as an additional model. Initially, a compilation of the YOLOv8 model, image input specifications, and batch sizes was provided. Subsequently, an iterative training process was conducted based on these configurations so that we can filter focus on parameters in Fig. 7(b).



(a) (b)

Fig. 6 (a) is a varies of parameter and (b) is a filtering of parameter optimization

Upon completion of the iteration encompassing all feasible hyperparameters, the model exhibiting the highest accuracy values was chosen for the assessment of model performance utilizing the validate dataset. Lastly, the configuration of the model was exported for practical application in subsequent work.

Table 2 Difference batch size parameter and performance

Parameter (yolov8n.pt)		epochs	lr	optimizer	val_acc
Image size	Batch size				
640	8	100	0.03223	adam	50.12%
	16	100	0.09760	adam	40.11%
	32	100	0.05515	adam	50.14%
	64	100	0.02956	adam	50.50%

In Table 2, the utilization of a low learning rate is indicative of the algorithm's preference for a methodical and gradual fine-tuning process of its knowledge repository, characterized by incremental adjustments to its cognitive framework. While this strategy may yield more accurate predictions, it could potentially require an extended period for complete absorption and proficiency in the subject matter under consideration. Consequently, for this scenario, we opt for a batch size of 64 in conjunction with the Adam optimizer, operating under the assumption that this configuration will yield superior performance metrics in following charts.

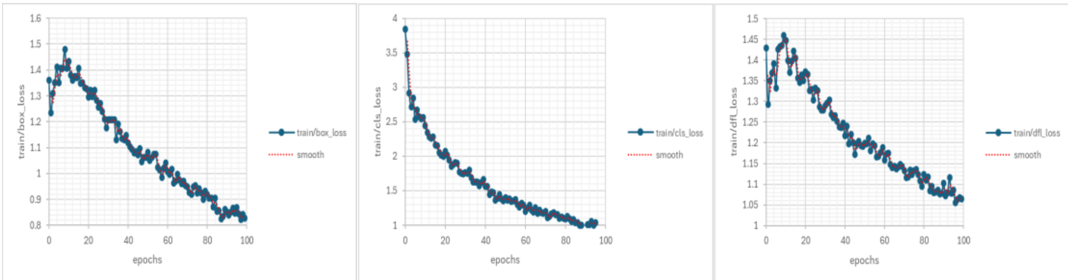
Object loss is a function that helps predict the bounding box and determine the best fit during inference. Fig. 8 the box loss, classification loss and distribution focal loss are obtaining the best intersection over union (IoU) between the object-bounding box and prediction. The machine learning method expects the lowest loss and high precision, recall, and specific metrics in object detection.

The custom dataset uses “yolov8n.pt” for the weight model and input the training images and corresponding annotations into the model with transfer learning. Adjust the model's weights through optimization and save the best model for later utilization. It depends on parameters such as task, mode, and model. It is easy to utilize for this experiment. Usually, we need to use the supported task of YOLOv8 for inference, validation, and training. It depends on our tasks experiment and fine-tune for the CSI model in the next step.

D. *Evaluation Matrices*

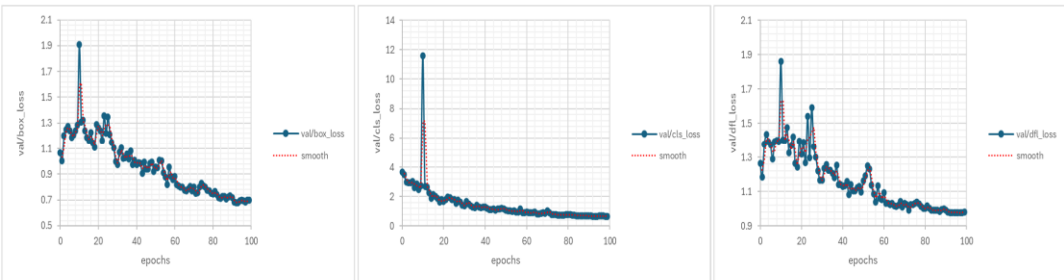
Both precision and recall are important metrics, and their relative importance depends on the specific task. To have a comprehensive evaluation, precision and recall are often combined into a single metric following.

After initializing the “yolov8n.pt”, it is a supplement model as the pre-trained weights dataset. In this step, the model learns to adjust weights to the specific features of our dataset and the objects that we need to detect. It will update to the “best.pt” model. We separate the dataset 80% for the training and 20% for the validation. So, this part needs to be input as an unseen dataset for validation on the best practices model with metric performance in Fig. 9 with algorithm reference formular (1), (2).



(a) (b) (c)

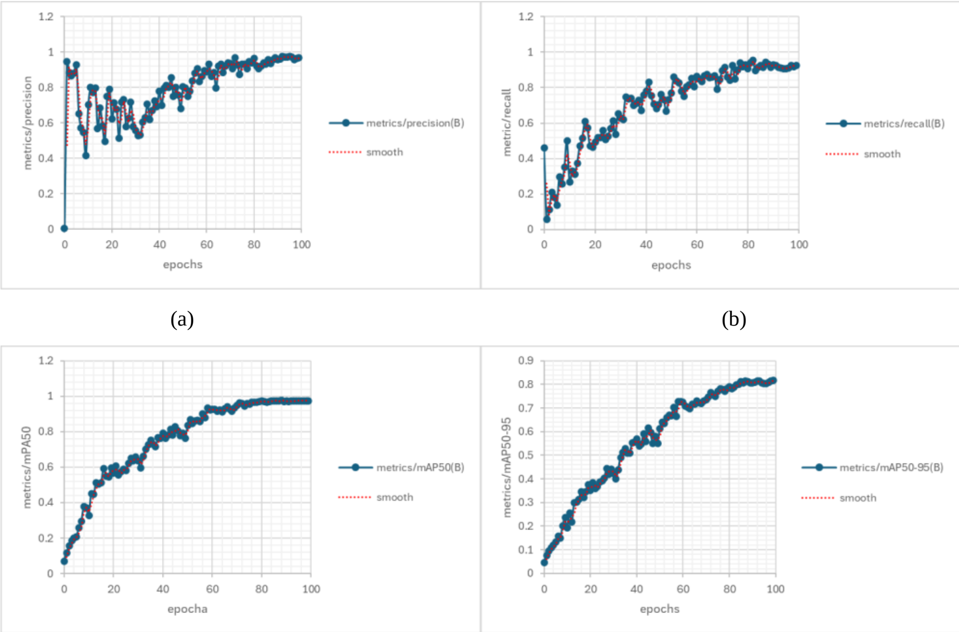
Fig. 8 (a) is a box loss, (b) is a class loss and (c) is a distribution focal loss in training process under the hyperparameter optimization condition



(a) (b) (c)

Fig. 9 (a) is a box loss, (b) is a class loss and (c) is a distribution focal loss in validation process under the hyperparameter optimization condition

Mean Average Precision(mAP) is a performance and evaluation object detection based on Confusion Matrix, Recall, Precision, and Intersection over Union (IoU). YOLOv8 also uses mAP to evaluate the accuracy and performance of their models.



(a) (b)

(c) (d)

Fig. 10 Results of metrices performance (a) is a metrics/precision, (b) is a metrices/recall, (c) is a metrics/mAP50 and (d) is a metrices/mPA50-95

YOLOv8, short for "You Only Look Once vesion 8" is a deep learning algorithm that assesses the performance of object detection models through the analysis of mean average precision (mAP). The utilization of mAP as a metric in this context proves to be highly dependable when it comes to the comparison of various models and the assessment of enhancements made to them. In the subsequent stages of the process, meticulous fine-tuning of hyperparameters is conducted within the framework of YOLOv8, contributing further to the optimization of the models under scrutiny.

In the COCO object detection evaluation document, AP and mAP are the same methods. However, mAP is calculated by finding the Average Precision (AP) for each class and then averaging over classes as follows.

$$mAP = \frac{1}{N} \sum_{i=0}^{N} AP_i \qquad (2)$$

where:

- N is number of classes
- AP_i is the average precision of class i

The mAP50 and mAP50-95 are performance and evaluate model measurement metrics. The mAP50 is the mean average precision at a threshold of 0.5 of IoU, while the mAP50-95 is a threshold ranging from 0.5 to 0.95 of IoU. A higher mAP50 or mAP50-95 indicates better performance of an object detection model[31].

However, Object Detection performance commonly used evaluation metrics in machine learning, and data classification. They are particularly important in tasks where the goal is to identify specific classes or categories within a dataset in model performance represented in precision, recall and F1-score in (3),(4),(5) .

Both precision and recall are important metrics, and their relative importance depends on the specific task. To have a comprehensive evaluation, precision and recall are often combined into a single metric following in .

Precision measures the accuracy of the positive predictions made by a model. In other words, precision quantifies how reliable the positive predictions are.

$$Precision = \frac{TP}{TP+FP} \qquad (3)$$

Where:

- *TP is True Positive*
- *FP is False Positive*

Recall is a sensitivity or true positive rate, measures the ability of a model to find all the relevant positive instances in a dataset. In other words, recall quantifies how complete the positive predictions are.

$$Recall = \frac{TP}{TP+FN} \qquad (4)$$

Where:

- *TP is True Positive*
- *FN is False Negative*

F1-score is the harmonic means of precision and recall, providing a balanced assessment of the model's efficiency.

$$F1 - Score = \frac{2*(Precision* \ Recall)}{Precision+Recall} \quad (5)$$

Overall model efficiency metrics illustrate in experiment result part.

E. Experiment Result

This section covers the simulation and experimental results obtained in this paper. The comparison of the proposed YOLOv8 with its pytorch model is presented based on mAP, recall, F1-Score, and model efficiency.

This experiment used a small volume of custom datasets and did not cover all objects because we could not acquire enough images. It shows only the possibility of expanding this technique in crime scene investigation. Furthermore, we can later implement it for analysis with other objects at the crime scene with a firm dataset in the crime scene investigation department. This experiment's results are incredible but keep in mind there are not enough datasets of YOLO's recommendations. It is a custom dataset. However, it shows trends and the possibility of using this technique in crime scene investigations and can improve with a large dataset later.

The training started with supported task “yolov8n.pt” (nano-size model). In the local experiment, GPU Nvidia RTX 3060 Series was used. The training time depends on hardware, size, epochs, and volume of image. Fig. 8 and 9 are model training, validation under hyperparameter optimization parameter and Fig. 10 are metrics performance of training model.

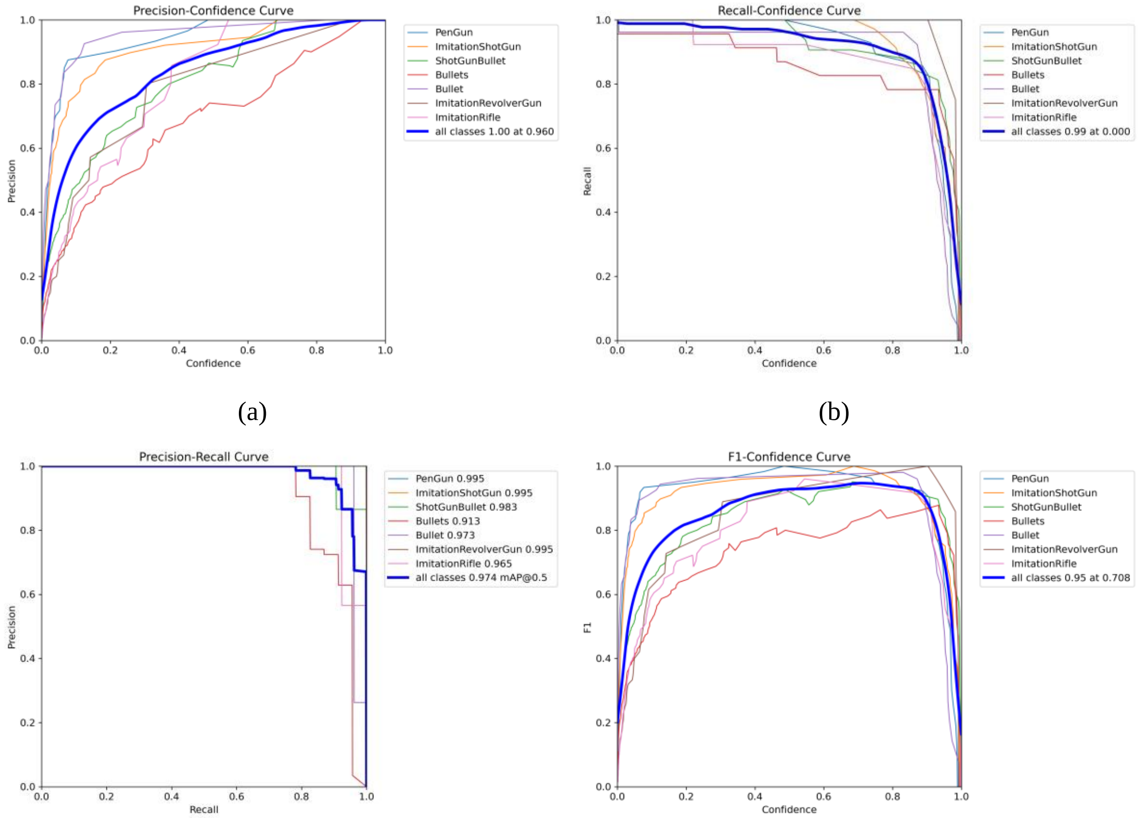


Fig. 11 (a) is a Precision-Confidence Curve, (b) is a Recall-Confidence Curve, (c) is a Precision-Recall Curve and (d) is a F1-Confidence Curve

Fig. 11(a) and 11(b) visually demonstrate the levels of precision attained across all classes, revealing a uniform value of 1.00 when the confidence level is set at 0.96. Furthermore, the recall performance across all classes is

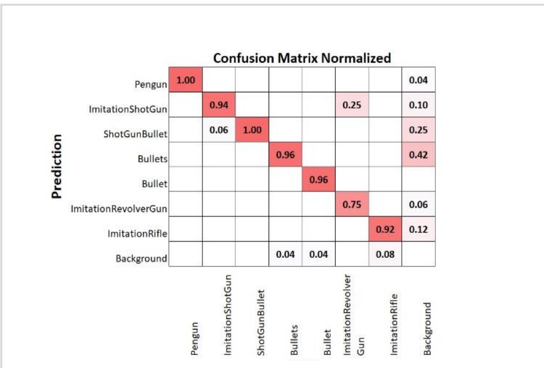


Fig. 12 Confusion matrix normalized of pen guns, illegal firearms, and related objects prediction

highlighted to be at a commendable level of 0.99 specifically at the confidence level of 0.00.

Fig. 11(c) and 11(d) visually present the mean Average Precision (mAP) values corresponding to all classes, which have been calculated to be 0.974 with a confidence threshold set at 0.5. Similarly, the F1 scores for all classes are depicted in these figures, indicating a value of 0.95 when the confidence threshold is adjusted to 0.708.

Fig. 12 shows the confusion matrix normalized of pen guns, illegal firearms, and related objects prediction—the highest confusion matrix normalized of 1.0 for classes of *PenGun* and *ShotGunBullet*. The confusion matrix normalized is 0.96 for the class Bullets and Bullet. The confusion matrix normalized are 0.94 and 0.92 for the class *ImitationShotGun* and *ImitationRifle*, respectively, and the lowest confusion matrix normalized are 0.75 for *ImitationRevolverGun*. It means that some misdetection on images.

The experimental procedure outlined in this study encompasses the implementation of a training regimen spanning across a total of 100 epochs, during which the loss function is applied to both the training and validation datasets. Nevertheless, an interesting observation has been made regarding certain discrepancies evident in the results, indicating instances of inaccuracies in the predictive capabilities of the model. The overall validation performance is shown in Table 3 from validation dataset with all classes in precision, recall, mAP50 and mAP50-95 in box detection.

Table 3 Results of validation dataset with all classes of precision, recall, mAP50 and mAP50-95 in box detection

Classes	Images	Instances	Box(P	R	mAP50	mAP50-95)
All	49	161	0.97	0.926	0.974	0.817
PenGun	49	28	1	0.934	0.995	0.844
ImitationShortGun	49	35	1	0.984	0.995	0.9
ShortGunBullet	49	32	1	0.899	0.983	0.782
Bullets	49	23	0.855	0.826	0.913	0.652
Bullet	49	26	0.993	0.962	0.973	0.8
ImitationRevolverGun	49	4	0.939	1	0.995	0.945
ImitastionRifle	49	13	1	0.881	0.965	0.795

After the process of fine-tuning the newly developed model is completed, the system automatically stores the most recent version of the fine-tuned model under the filename "best.pt", signifying its optimization for future usage. Subsequently, there is the possibility to design and implement an interactive user interface for an application that will effectively harness the superior capabilities of the best Crime Scene Investigation (CSI) model at a later stage. It is conceivable to draw parallels and establish similarities with other forms of corroborative evidence, thereby reinforcing the notion that the same procedural approach employed in the domain of crime scene investigation can be extrapolated and applied in a broader context.

During the evaluation phase, it was observed that certain outcomes exhibited a diminished level of accuracy in terms of detection rates, primarily attributable to the limitations of the dataset which lacks comprehensive coverage of a diverse range of perspectives for the purposes of training. The inclusion of images sourced from online platforms depicting items such as pen guns, illicit firearms, and related paraphernalia arranged conspicuously on the surface in various news articles served as a valuable resource for enhancing the dataset. Nevertheless, the experimental trial yielded favorable results in the testing phase, as evidenced by the precision metrics ranging from 0 to 1 (equivalent to 0-100%) delineated in the graphical representation presented in Fig.13. Some detection is precision metrics ranging should be presented with point to the example due to above reasons.

Fig. 13 Sample of results of testing related objects prediction

The findings indicate the presence of additional geometric forms which are distinguished through manual observation. One such form is characterized by a white triangular shape, specifically pointing towards instances of low confidence of true predictions, identified at a rate of 60%. Furthermore, there is a particular shape resembling a red arrow, which serves as an indicator for cases of misprediction, albeit with a lower confidence level of 30%. However, it is worth noting that all classes exhibit a high level of accuracy in their predictions in Table 2, thereby suggesting the potential for their utility in the context of crime scene investigation.

4. Discussion

These inaccuracies stem from the model's tendency to misclassify objects based on the Intersection over Union (IoU) metric, particularly in cases where the background present in the images plays a significant role. Notably, the primary source images utilized in this study are sourced from police news reports and websites, each depicting various scenarios where objects are juxtaposed and overlapping on a flat surface. Consequently, this overlapping nature of objects has led to instances of misdetection in certain images, thereby contributing to a reduction in the overall accuracy of the model's predictions.

The problems of the custom dataset are small datasets and overlapping between pen guns, illegal firearms, and other objects in the annotation process. So, the system trains and detects different objects, such as the various

5. Conclusion

The experimental findings demonstrate promising trends and a satisfactory degree of confidence that can be applied within the domain of forensic investigation. It is important to highlight, nonetheless, that meticulously curated, high-quality, diverse, and extensive datasets may lead to even more significant improvements in the effectiveness of instructional processes and the accuracy of results. Given this point of consideration, the results hold the promise of being integrated into pragmatic, real-world situations, particularly in the field of forensic investigation, although they may not be suitable for small objects; nevertheless, we have the opportunity to refine the methodology in this context at a later stage.

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