Handgun Object Detection with YOLOv8

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December 22, 2023

Abstract

This study represents handgun object detection using the new state-of-the-art and latest version of YOLO (You Only Look Once) algorithm from Ultralytics, applied through video in different environments demonstrating high accuracy and effectiveness. The system can serve as a security measure in public spaces providing a more secure and reliable handgun detection.

1 Introduction

In today's society, more people can have the accessibility to firearms for security purpose while on the other hand has a great potential of being misuse for illegal activities such as violence and criminal acts. The challenge is to address the risk associated with firearms and protect the life of people while also providing more secure public spaces. By providing the detection of handguns law enforcement can anticipate crimes, have better and quicker responses which could minimize harm and losses. This can also help in the decision making for lawn enforcement which can give a more detail information of the overall situation to make the right choice at the moment. Crowed places such as schools, malls, and airports can benefit from this approach and ensure the safety of these individuals. The fact of going out having this extra layer of security like a real-time guardian can provide a piece of mind for most people.

2 Method

The use of technology is spreading and growing while improving daily for all type of different tasks. The approach used to provide a solution for these type of problems is using one of the best and latest version of object detection algorithm YOLOv8 from Ultralytics [JCQ23]. The model was build from previous versions of YOLO having a better performance designed to be fast, accurate, and easy to use with a wide range of object detection. By using this improved version of the algorithm, the model can be trained with a custom data set to capture real-time, image or video. After the model has been trained and evaluated it can check unseen data to point out a confidence score with a bounding box describing the probability of capturing a handgun.

There are some challenges to face to provide proper training to the model. A few example of these can be the handling of a pistol, this action can vary from using one or two hands with different amount of range while handling. Another difficulty is the process of designing the dataset manually and labeling. When the algorithm detects a handgun should have a good confidence score of at least greater than 0.5 to not give false detection.

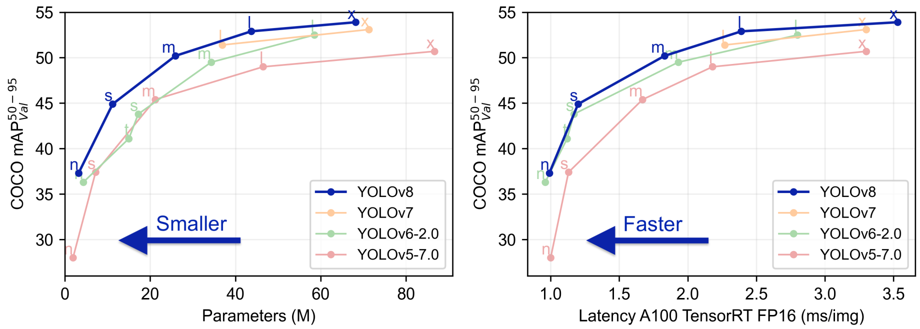
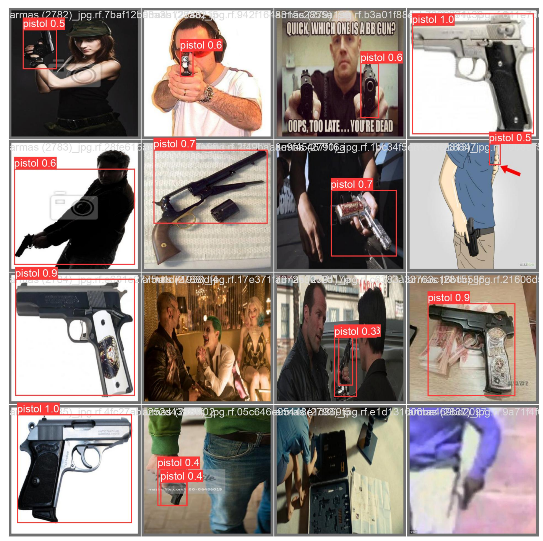


Figure 1: Comparison of YOLO different versions with COCO dataset

3 Experiments

(a) Label



(b) Prediction

Figure 2: Custom Dataset Labeling and Prediction

3.1 Dataset

The data set used in this experiment is provided by the University of Granada research group to perform weapon detection tasks through different approaches classified in handguns, knives, and weapons vs similar handle object. For the purpose of this experiment only the data of handguns is used. The dataset contains 2986 images and 3448 labels across a single annotation class denoted as pistols. The images are wide-ranging from pistols in-hands, cartoons, and staged studio quality images of guns.

3.2 Evaluation metrics

To evaluate the performance of the model different metrics are being used. To identify the number of true positives, true negatives, false positives, and false negatives a confusion matrix is used. By obtaining these values other metrics can be derived such as accuracy, precision and recall. For object detection loss a box loss to measure the error in predicting the coordinates of the bounding boxes is used as well as a class loss that quantifies the error inn predicting the object class for each bounding box. Finally, a defocus loss is also being used to improve the object detection in scenarios with defocused or blurry images. Also, YOLO provides a mean average precision score (mAP) that considers both precision and recall object class. mAP50 focuses on an intersection over union (IoU) threshold of 0.5 which can measure how well the model identifies overlap and to provide even better results it give mAP95 which is an extension of the evaluation threshold from 0.5 to 0.95.

3.3 Results

(a) Detection of handguns with shoot position

(b) Frontal part of a handgun

Figure 3: Object Detection of Handgun After Training with YOLOv8

3.4 Analysis and discussions

The algorithm demonstrates notable proficiency when applied to the custom dataset, while showing a moderate to high accuracy in the detection of handguns. The comprehensive metric evaluations conducted on the model to have a deeper understanding of the performance, particularly in terms of high accuracy and precision involves a training of approximately 50 epochs, utilizing a batch size of 16 and leveraging the Adam Optimizer to minimize loss. The last recorded mean Average Precision (mAP50) stands at an impressive 0.88, while mAP50-95 indicates a value of 0.71. These metrics signify the model's effectiveness, but there is potential for improvement by fine-tuning hyperparameters and expanding the dataset with additional images for training.

In the earlier training phase of 10-20 epochs, the model demonstrated a peak performance between epochs 30 and 50 concerning mAP50 and mAP50-95. Despite delivering overall satisfactory detection capabilities of the algorithm, the model struggled to capture the object adequately or, in some cases, failed to detect it altogether. These observations suggest that the model's performance can benefit from further optimization and parameter tuning to enhance its performance and reliability when it comes to capturing the handguns in different scenarios and challenges.

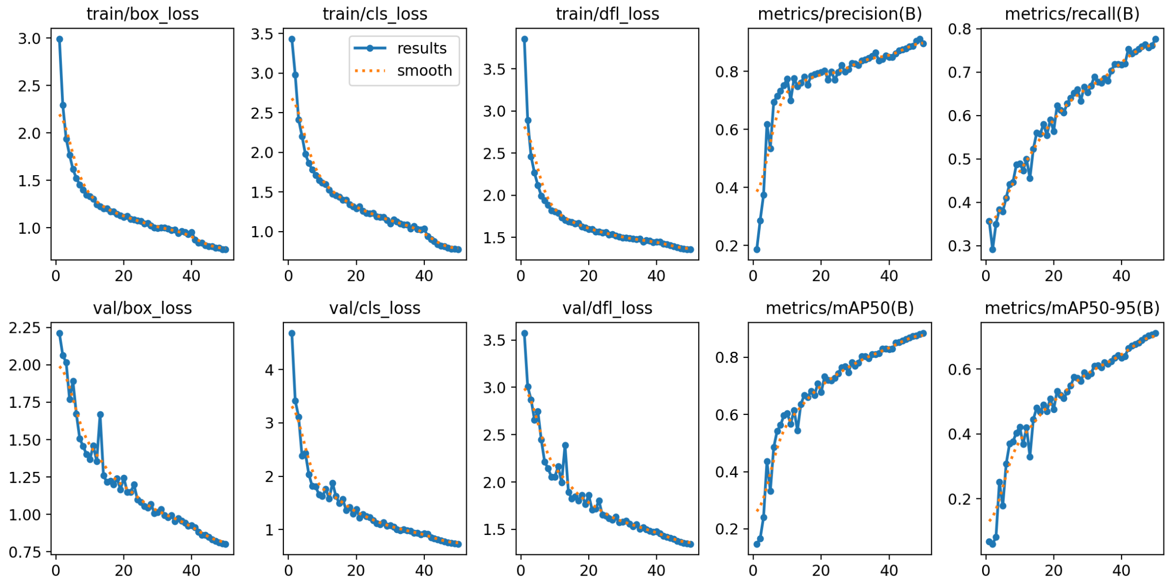
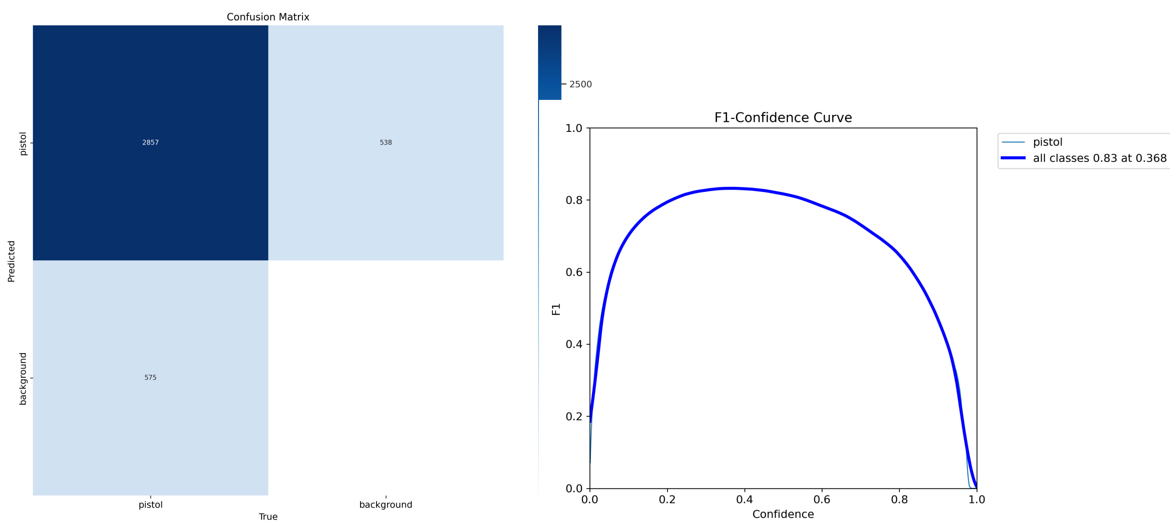


Figure 4: Results of Model Evaluation After Training



(a) Confusion matrix

(b) F1-Confidence Curve

Figure 5: Extra Results of Model Evaluation

4 Conclusion

The algorithm You Only Look Once (YOLO) has demonstrated its incredible performance on a custom dataset. It has proven to be effective addressing security concerns by accurately identifying handgun object showing a moderate to high level of accuracy. There is still an ample room for improvement the model making it more diverse and optimal. Tuning the hyperparameters, optimizing the training process, and expanding the dataset are just a few examples that can potentially enhance the model capabilities. Of course, there are also other tools in computer vision than can be combined with the handgun detection to provide even a better a more precise goal. Overall technology will keep developing and more and different approach might also help security concerns to provide peace of mind.

References

[JCQ23] Glenn Jocher, Ayush Chaurasia, and Jing Qiu. YOLO by Ultralytics, January 2023.