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Analysis Of YOLO Algorithm For Long And Short Firearm Detection

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Abstrak

Deteksi senjata api di ruang publik merupakan tantangan keamanan yang memerlukan solusi otomatis dan andal. Metode object detection berbasis deep learning, khususnya algoritma You Only Look Once (YOLO), telah terbukti mampu mendeteksi objek berbahaya secara cepat dan akurat. Penelitian ini bertujuan menganalisis kinerja YOLOv11, versi terbaru YOLO yang menawarkan peningkatan akurasi dan efisiensi dibandingkan YOLOv8, dalam mendeteksi senjata api jenis laras panjang (long gun) dan laras pendek (short gun). Model YOLOv11 dilatih menggunakan dataset sebanyak 11.969 citra yang dibagi menjadi data pelatihan, validasi, dan pengujian, serta didukung augmentasi data berupa rotasi, grayscale, blur, pengaturan brightness dan exposure, serta penambahan noise. Pelatihan dilakukan selama 100 epoch dengan ukuran citra 640 × 640 piksel dan batch size 8. Hasil pengujian menunjukkan YOLOv11 mencapai precision 91,3%, recall 85,9%, mAP@50 92,2%, dan mAP@50–95 78,6%, dengan F1-score 98% untuk long gun dan 97,5% untuk short gun. Pengujian pada berbagai kondisi citra menunjukkan performa yang stabil dan cukup robust, meskipun terjadi penurunan kinerja pada citra dengan noise 50% dan jarak pengujian 2 meter. Penelitian ini menunjukkan bahwa YOLOv11 unggul dibandingkan versi sebelumnya dan berpotensi kuat untuk diterapkan pada sistem pengawasan keamanan berbasis real-time di lingkungan publik.

Kata kunci*— YOLOv11, deteksi objek, senjata api, long gun, short gun, deep learning*

Abstract

Firearm detection in public spaces is a security challenge that requires an automated and reliable solution.Firearm detection in public spaces is a security challenge that requires an automated and reliable solution. Deep learning-based object detection methods, particularly the You Only Look Once (YOLO) algorithm, have proven capable of detecting dangerous objects quickly and accurately. This study aims to analyze the performance of YOLOv11, the latest version of YOLO offering improved accuracy and efficiency compared to YOLOv8, in detecting long guns and short guns. The YOLOv11 model was trained using a dataset of 11,969 images divided into training, validation, and testing data, supported by data augmentation techniques including rotation, grayscale, blur, brightness and exposure adjustment, and noise addition. Training was conducted for 100 epochs with an image size of 640 × 640 pixels and a batch size of 8. The test results show that YOLOv11 achieved a precision of 91.3%, a recall of 85.9%, an mAP@50 of 92.2%, and an mAP@50–95 of 78.6%, with an F1-score of 98% for long guns and 97.5% for short guns. Testing under various image conditions demonstrated stable and robust performance, despite a decline in detection results on images with 50% noise and at a testing distance of 2 meters. This study demonstrates that YOLOv11 outperforms its predecessors and shows strong potential for deployment in real-time surveillance and security systems in public environments..

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Keywords— *YOLOv11, object detection, firearm, long gun, short gun, deep learning*

1. INTRODUCTION

Indonesia is a country with a high level of security dynamics, in line with increasing community activities and technological developments [1]. One of the serious challenges in the field of security is the misuse and circulation of firearms, both in criminal acts and threats to vital facilities. The presence of firearms in public and restricted environments poses a significant risk to human safety and security stability [2]. Therefore, a surveillance system capable of detecting the presence of firearms quickly and accurately is needed. However, in practice, the security monitoring process still relies heavily on manual surveillance through CCTV cameras, which are highly dependent on the vigilance of officers and have limitations in detecting dangerous objects in real-time [3]. This condition shows the need to apply smart technology that can help improve the effectiveness of security systems through automatic firearm detection.

One way to detect dangerous objects, especially firearms, is by applying image processing [4]. Image processing is a rapidly developing field of research, where real-time observation systems provide opportunities for researchers to develop new research on various issues in the field of security [5]. The processing carried out in image processing is object detection, which is implemented to detect the presence of certain objects [6]. Object detection is related to the process of identifying objects in the real world, such as humans, vehicles, and dangerous objects [7]. Object detection algorithms utilize various image processing techniques to extract the parts of objects that are the focus of observation [8]. Object detection can be implemented in security systems to detect threats, one of which is the presence of firearms [9]. One algorithm that has been implemented for object detection and is capable of producing good results is You Only Look Once (YOLO).

The YOLO algorithm is a deep learning algorithm used to detect objects by dividing the input image into several grids [10]. Each grid is responsible for predicting the bounding box, object confidence score, and class probability of the detected object, so that YOLO output can generate object location and class information simultaneously in one processing stage. YOLO is known as one of the object detection methods that has high processing speed with good performance and high accuracy compared to other object detection methods, making it very suitable for application in real-time surveillance systems [11].

In previous research, YOLO has been implemented for the detection of dangerous weapons in images. A study using YOLOv8 for firearm detection reported a precision of 84%, a recall of 77%, an mAP of 84%, and an F1-score of 88% [12]. Further studies on firearm detection under various distorted image conditions also demonstrated that YOLO-based models are capable of maintaining stable detection performance across challenging scenarios [13]. Although these results are promising, YOLOv8 still has notable limitations in terms of inference speed, memory efficiency, and detection accuracy for small and partially occluded objects, particularly under challenging real-world conditions such as noise, low lighting, and varying distances. These limitations highlight the need for a more advanced model capable of delivering higher accuracy and greater robustness in real-world surveillance applications.

YOLOv11, as the latest generation of the YOLO architecture, addresses these shortcomings through the introduction of C3k2 blocks, an enhanced Spatial Pyramid Pooling Fast (SPPF) module, and a C2PSA attention mechanism, which collectively improve feature extraction and detection performance while maintaining computational efficiency [14][15]. A comprehensive review of YOLO variants from YOLOv1 to YOLOv11 confirms that each successive version has consistently improved detection accuracy and inference speed, with YOLOv11 achieving higher mAP while using fewer parameters compared to YOLOv8. Despite

these advancements, the application of YOLOv11 specifically for firearm detection, particularly with a focus on distinguishing between long guns and short guns, remains limited in the literature [16].

This study aims to analyze the performance of YOLOv11 in detecting two categories of firearms, namely long guns and short guns, using a dataset of 11,969 images with comprehensive augmentation techniques. The contributions of this study are as follows: (1) providing an empirical evaluation of YOLOv11 for firearm detection tasks, demonstrating its superiority over YOLOv8 in terms of precision, recall, and mAP; (2) analyzing model robustness across diverse image conditions including noise, rotation, grayscale, and varying distances; and (3) demonstrating the potential of YOLOv11 as a reliable component for deployment in real-time public surveillance and security systems.

2. METHODS

This study uses the YOLOv11 algorithm with a transfer learning approach, which allows the model to utilize knowledge from pre-trained weights that have been learned previously to be applied to new detection tasks. This approach utilizes the default model provided by YOLO, so that the training process can be carried out more efficiently without having to train the model from scratch using a new dataset [17]. The stages of the research included dataset collection, preprocessing and augmentation, YOLOv11 configuration, model training, and a final stage of evaluation and testing of the detection results.

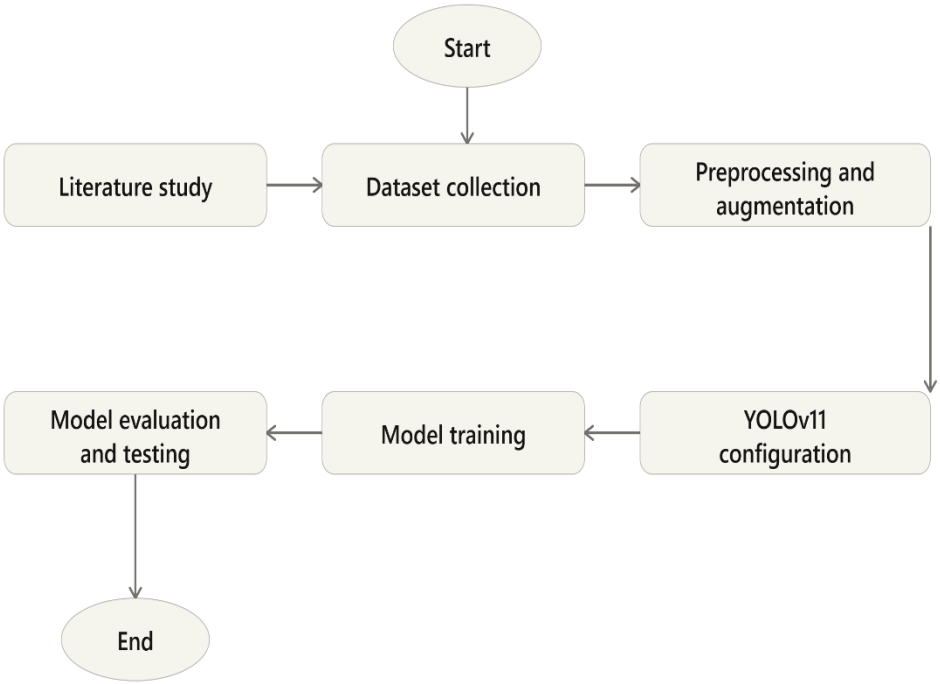


Figure 1 Flowchart of Research Stages

YOLOv11 is a further development of the You Only Look Once (YOLO) algorithm, which is designed to detect objects in images in near real-time with high accuracy and speed [18]. Compared to YOLOv8, YOLOv11 has advantages in inference speed, memory efficiency, and detection accuracy for small and complex objects. In general, YOLO divides the input image into several grids, where each grid is responsible for predicting the bounding box and object class probability [19].

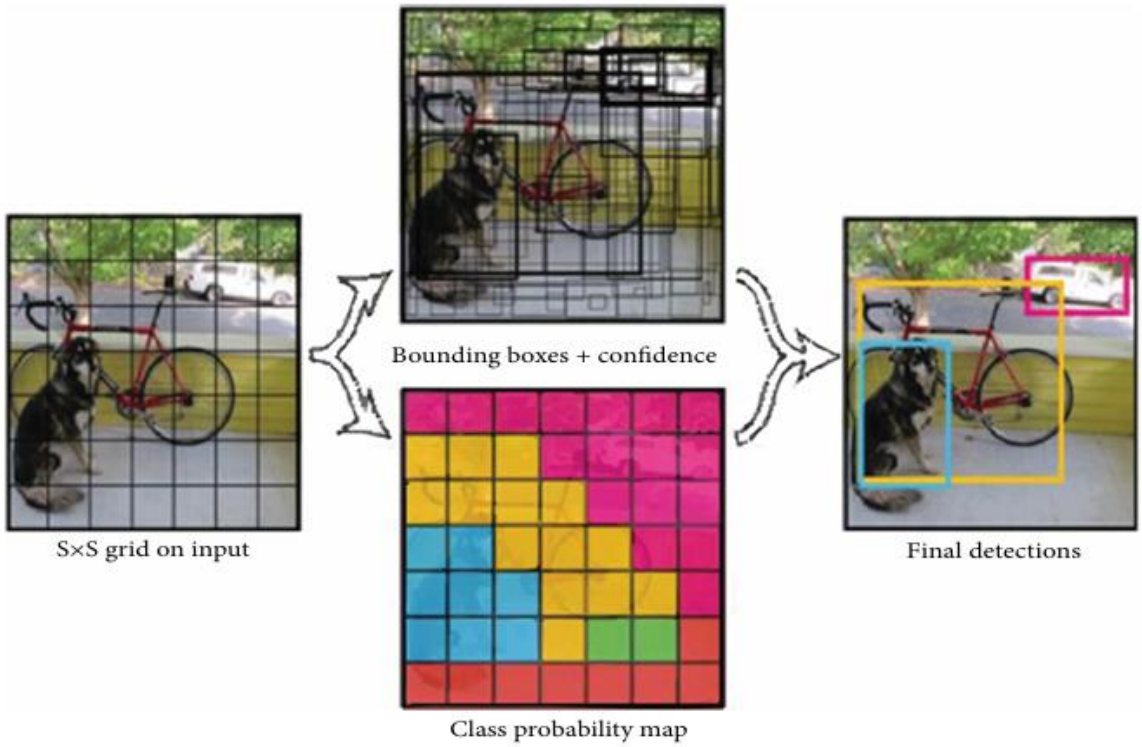


Figure 2 How the YOLO Algorithm Works (Source: Lv, 2025 [20])

2.1 Dataset Collection

The dataset in the object detection model is a collection of images used in the model training process. This study focuses on developing a weapon detection model, specifically for long guns and short guns, which aims to support surveillance and security systems. Therefore, the Roboflow platform is used to facilitate the process of collecting, managing, and preparing the dataset. The dataset used in this study consists of 11,969 images containing long guns and short guns. Details of the dataset division into training, validation, and testing data can be seen in Table 1.

Table 1 How the YOLO Algorithm Works

Jenis Data	Jumlah Citra
Data Pelatihan	10.473
Data Validasi	997
Data Pengujian	499

2.2 Preprocessing and Augmentation

The annotation and labeling process is one of the preprocessing stages in the dataset that aims to tag each image data. This tagging includes determining the bounding box coordinates [x][y] accompanied by class information [class] according to the type of object detected, as well as the width [w] and height [h] parameters of the object within the bounding box. In addition, the preprocessing stage also applies the Auto-Orient process to automatically adjust the image orientation and resize it using the stretch method to a size of 640 × 640 pixels. In this study, two object classes were used, namely long gun and short gun.

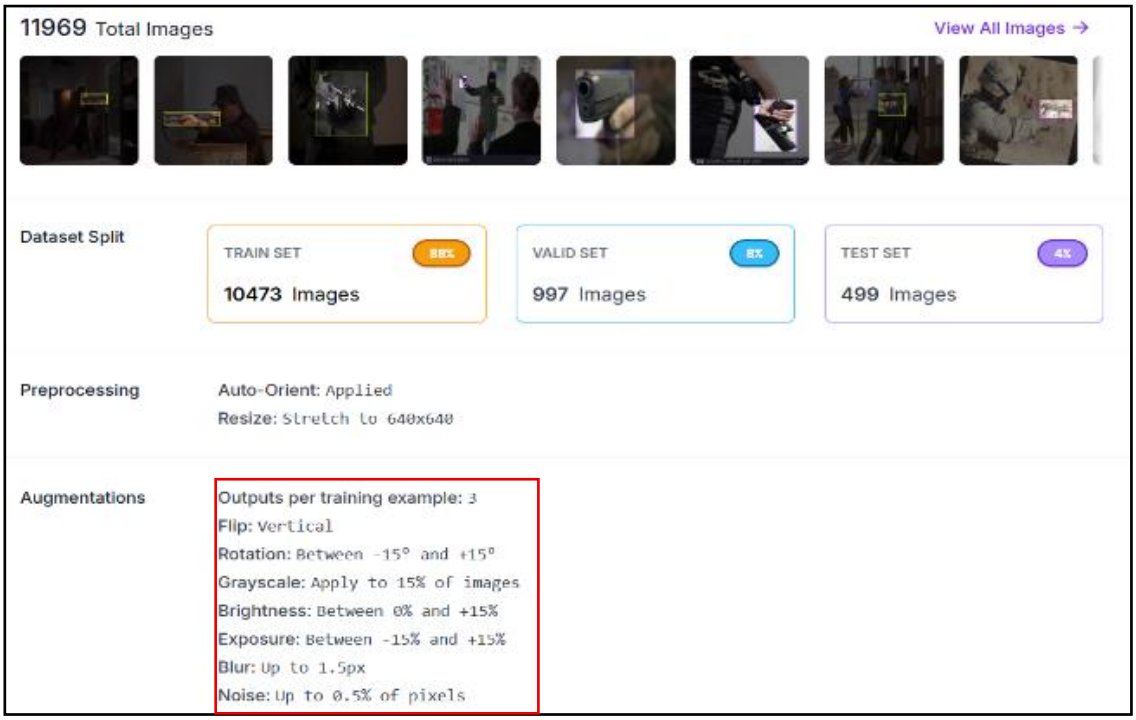


Figure 3 Preprocessing and Augmentation Techniques

Data augmentation is a stage in dataset preparation that aims to increase the amount and variety of data so that the dataset becomes richer [21]. In this study, each training data example produced three outputs (outputs per training example: 3). The augmentation techniques applied included vertical flip, rotation, grayscale, brightness exposure, blur, and noise. Each augmentation technique applied will cause changes in the position and shape of objects in the image [22].

2.3 YOLOv11 Configuration and Training

At this stage, the configuration and training of the YOLOv11 model were carried out using Anaconda as the package management environment and code execution medium, while Visual Studio Code was used as the code editor for writing and managing scripts. The configuration process begins with setting up the Anaconda environment and installing the Ultralytics library. The dataset that has undergone the labeling process on the Roboflow platform is downloaded in ZIP file format, extracted into the dataset folder, and used locally as training data. Hyperparameter configuration includes setting the image size to 640, the batch size to 8, and the number of epochs to 100. Next, the YOLOv11 model training process is run through Anaconda based on these configurations, followed by testing to evaluate the performance of the resulting object detection.

2.4 Evaluation and Detection Testing

Model performance evaluation was conducted using a confusion matrix to obtain precision, recall, mean Average Precision (mAP), and F1-score values. The confusion matrix serves as an evaluation tool that compares the model's prediction results with the actual data conditions [23]. This matrix consists of four main components, namely True Positive (TP) and True Negative (TN), which indicate correct predictions, as well as False Positive (FP) and False Negative (FN), which represent prediction errors.

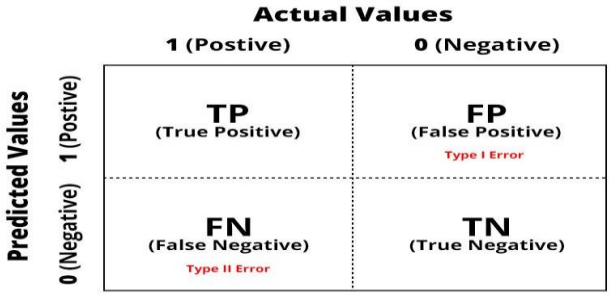


Figure 4 Four Components of the Confusion Matrix

To determine accuracy, measurements are taken of the model's accuracy in classifying the data as a whole. Accuracy shows how many predictions are correct, both positive and negative, compared to all the data tested. This is the ratio of correct predictions (positive and negative) to the total data [24]. The accuracy value provides a general overview of the model's performance, but it needs to be analyzed in conjunction with other metrics such as precision, recall, and F1-Score for a more comprehensive evaluation of the model's performance.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)[24]$$

Precision is an evaluation metric in model classification used to measure the accuracy of positive predictions generated by the model. This metric expresses the proportion of correct positive detections to all positive detection results [25]. Precision provides information about how accurately the model classifies an instance as positive, where a high precision value indicates a low number of false positives.

$$Precision = \frac{TP}{TP+FP} \quad (2)[25]$$

Recall or sensitivity (true positive rate) is one of the evaluation metrics used to assess the performance of a classification model. This metric shows the success rate of the model in identifying all data that truly belongs to the positive class in the dataset. This measure assesses the extent to which the model is able to accurately detect all positive examples found in the actual data [26].

$$Recall = \frac{TP}{TP+FN} \quad (3)[26]$$

The F1-score is an evaluation metric that integrates precision and recall values to provide a more comprehensive representation of classification model performance [27]. This metric is used to assess the balance between the accuracy of positive predictions and the model's ability to detect all positive data, especially in conditions where the distribution of positive and negative classes is imbalanced.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)[27]$$

Weapon detection testing was conducted using the Roboflow platform, which was used to run the previously trained model. This testing aimed to analyze the performance of the YOLOv11 model in detecting images of long gun and short gun under various image conditions. The aspects tested include images with a rotation angle of -15° and 15°, conversion to grayscale, application of blur, variations in brightness and exposure levels, addition of noise, and testing

based on the difference in distance between the object and the camera.

2.5 System Implementation

In this study, the system was implemented on the Visual Studio Code software platform as a code editor with program execution running through the Anaconda environment. The system was run on a Windows 10 operating system with AMD64 architecture, supported by an Intel® x64-based processor with 20 processing cores and 15.67 GB of main memory, as well as an NVIDIA GeForce RTX 3060 Laptop GPU with 6 GB of VRAM and CUDA version 13.0 support. The model implementation was carried out using Python version 3.11.14 with supporting libraries in the form of PyTorch 2.9.1 integrated with CUDA, OpenCV 4.12.0, and Ultralytics 8.3.241 as the YOLOv11 framework.

3. RESULTS AND DISCUSSION

3.1 Detection Test Results

The primary model evaluation was carried out on the main dataset consisting of 11,969 images divided into training, validation, and testing splits, from which the core performance metrics (precision, recall, mAP@50, and mAP@50-95) were derived. In addition to the primary evaluation, additional robustness testing was conducted using 14 images for long guns and 12 images for short guns obtained independently from the internet, outside the main dataset. This supplementary testing was designed to assess the model's generalization capability under diverse real-world image conditions, rather than to serve as the primary performance benchmark. Testing was carried out by applying various image conditions, including rotation angles of −15° and 15°, grayscale, blur, brightness, exposure, noise, and differences in distance between the object and the camera.

Detection tests on normal images showed that the YOLOv11 model was able to produce consistently high confidence values, with a confidence range of 91% to 97% for long gun detections and 90% to 95% for short gun detections. In the case of long gun, all 14 test images were successfully detected with an average confidence of 94%, while in the case of short gun, all 12 test images were accurately recognized with an average confidence of 92%, including images containing more than one object in varying positions.



Figure 5 Weapon Detection Results on Normal Images

Detection testing on images with rotation angles of −15° and 15°, as shown in Figure 6, produced fairly good performance. In the three long gun images, the confidence values obtained ranged from 84% to 94%, while in the three short gun images, the confidence values ranged from 86% to 91%. These results indicate that the YOLOv11 model is still capable of reliable detection despite changes in object orientation.

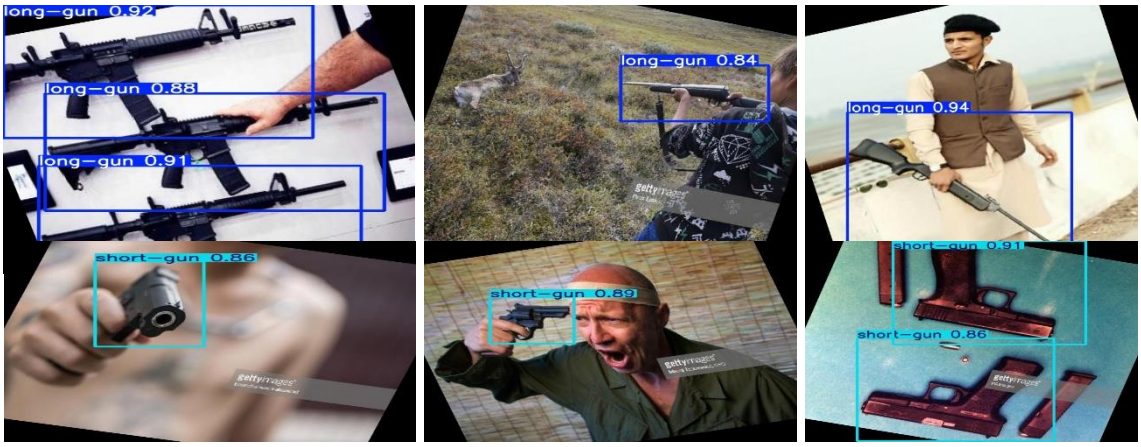


Figure 6 Weapon Detection Results on Rotated Images

Furthermore, detection testing on grayscale images shows that the confidence values produced are relatively the same as testing on normal images. This indicates that converting images to grayscale does not significantly affect the ability of the YOLOv11 model to detect weapon objects.

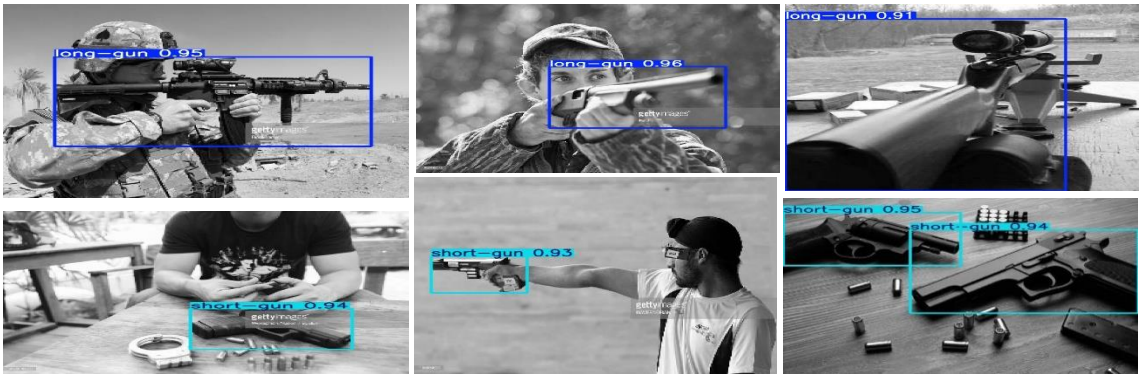


Figure 7 Weapon Detection Results on Grayscale Images

In detection testing using images with a blur level of 6 px as shown in Figure 8, the YOLOv11 model was still able to detect long gun and short gun well. For long gun, confidence values of 92%, 93%, and 90% were obtained, while for short gun, confidence values of 92%, 93%, and 93% were obtained. These results indicate that applying blurring up to 6 px does not significantly reduce the detection performance of the model.



Figure 8 Weapon Detection Results on Blur Images

Based on the test results on images with a brightness level of 100%, the YOLOv11 model is still able to detect long gun and short gun optimally. In the long gun class, the confidence values produced ranged from 88% to 91%, while in the short gun class, the confidence values ranged from 88% to 94%. These confidence value ranges are in the very good category, indicating that increasing the brightness level of the image does not have a significant effect on the model's detection performance. Thus, the YOLOv11 model can be said to be quite robust against changes in brightness in the input image.



Figure 9 Weapon Detection Results on Brightness Images

Furthermore, in image detection testing with 100% exposure as shown in the image, the YOLOv11 model was still able to detect long gun and short gun objects with excellent performance. The confidence values produced for both object classes were above 90%, indicating that the increase in exposure did not have a significant impact on the model's detection capabilities. These results confirm that YOLOv11 has excellent robustness against changes in exposure levels in the input image.



Figure 10 Weapon Detection Results on Exposure Images

In detection testing using 50% noise applied to images as shown in the figure, the YOLOv11 model experienced a decline in detection performance. This decline occurred mainly in long gun objects, with confidence values ranging from 79% to 82%, which can still be categorized as quite good. Meanwhile, for the short gun object class, the model continued to perform very well with confidence values ranging from 83% to 95%. These results show that the addition of noise affects detection performance, especially for long gun objects, but the YOLOv11 model is still able to maintain relatively stable detection performance.



Figure 11 Weapon Detection Results on Noise Images

Finally, in detection testing with an image capture distance simulation of 2 meters, the YOLOv11 model was still able to detect long gun and short gun objects with relatively good performance. In the long gun class, the confidence value produced was in the range of 85%–94%, and the model successfully detected two long gun objects in the image. Unlike the long gun class, detection of short gun objects decreased in the first image, with a confidence value in the range of 76%–82%, but the model was still able to detect all five short gun objects in the image. Furthermore, in the second image containing two short gun objects, the confidence value increased to 84% and was categorized as good, while in the third image containing only one short gun object, the confidence value reached 88% and was categorized as very good. These results show that increasing the image capture distance affects the detection confidence level, especially for short gun objects, but the YOLOv11 model is still able to maintain consistent object detection capabilities.



Figure 12 Weapon Detection Results at a Distance of 2 Meters

3.2 Confusion Matrix

The confusion matrix is used to evaluate the performance of the YOLOv11 model in classifying objects based on predetermined classes. This matrix provides an overview of the relationship between the model's prediction results and the actual labels, so that the number of correct predictions and classification errors in each class can be determined. Through the confusion matrix, the model's performance in distinguishing weapon objects can be analyzed in more detail, particularly in identifying the values of true positive, false positive, false negative, and true negative as the basis for calculating evaluation metrics.

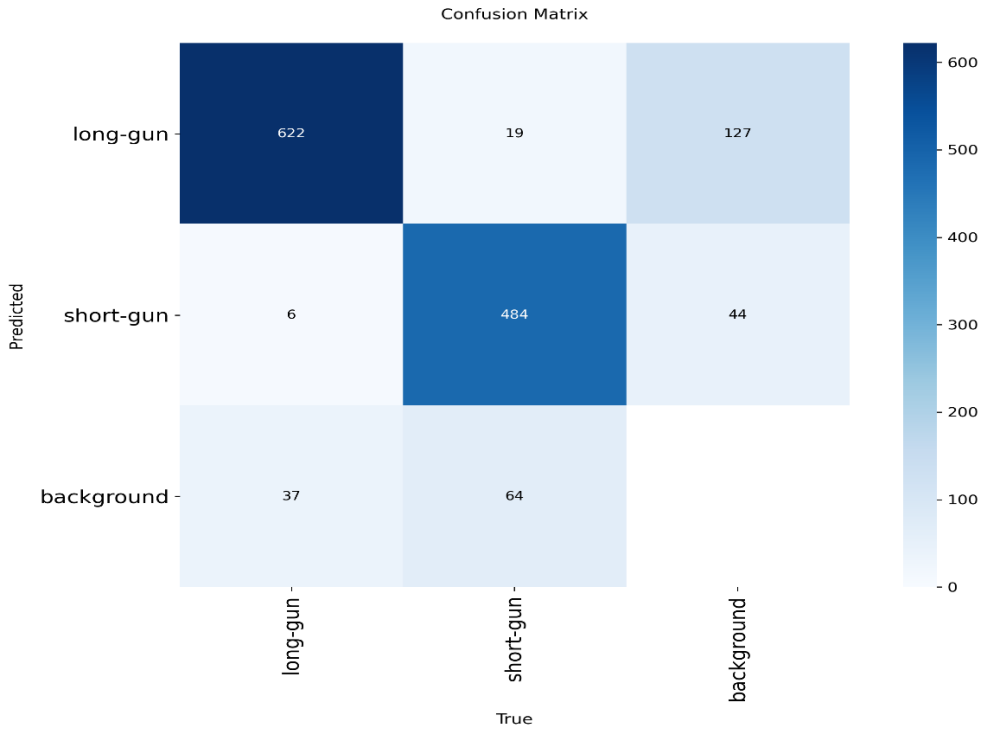


Figure 13 YOLOv11 Confusion Matrix Results

Based on Figure 13, the prediction results of the YOLOv11 model for each class can be analyzed in more detail through the true positive (TP), false positive (FP), false negative (FN), and true negative (TN) values. Details of the analysis results can be seen in Table 2.

Table 2 Confusion Matrix Analysis Results

Class	True Positive (TP)	True Negative (TN)	False Postive (FP)	False Negative (FN)
Long Gun	622	484	6	19
Short Gun	484	622	19	6

Based on Table 2, it can be seen that the YOLOv11 model is capable of classifying long gun and short gun objects with a high prediction rate, as indicated by the dominance of true positive and true negative values in each class. Furthermore, these values are used to calculate evaluation metrics such as accuracy, precision, recall, and F1-score to quantitatively assess the model's performance in each class, the results of which can be seen in Table 3.

Table 3 Confusion Matrix Evaluation Metrics Results

Class	Accuracy	Precision	Recall	F1-Score
Long Gun	97,79%	99,04%	97.04%	98%
Short Gun	97,79%	96,22%	98.78%	97,5%

The YOLOv11 model showed excellent performance in both classes, with high accuracy, precision, recall, and F1-score values, enabling it to accurately detect long gun and short gun objects.

3.3 Accuracy of the YOLOv11 Model

The YOLOv11 model was trained for 100 epochs with an image size of 640 × 640 pixels. The training results were reviewed based on precision, recall, and mAP@50 values to evaluate the model's accuracy, as shown in Table 4.

Table 4 Model Training Results for Each Epoch

Epochs	Precision	Recall	mAP50	mAP50-95
10/100	0.768	0.599	0.702	0.501
20/100	0.802	0.752	0.816	0.609
30/100	0.864	0.752	0.861	0.687
40/100	0.880	0.818	0.900	0.733
50/100	0.891	0.840	0.908	0.750
60/100	0.903	0.842	0.914	0.763
70/100	0.912	0.845	0.916	0.774
80/100	0.920	0.857	0.922	0.780
90/100	0.915	0.866	0.922	0.783
100/100	**0.913**	**0.859**	**0.922**	**0.786**

Based on Table 4, the performance of the YOLOv11 model improves as the number of training epochs increases, as shown by the increase in precision, recall, mAP50, and mAP50–95 values up to the 100th epoch. At the end of training, the model achieved precision of 0.913, recall of 0.859, mAP50 of 0.922, and mAP50–95 of 0.786, indicating that the training process has produced stable and convergent performance.

4. CONCLUSIONS

The results of training the YOLOv11 model in this study show excellent performance in detecting long guns and short guns. Based on the evaluation results, the model achieved a precision value of 91.3%, a recall of 85.9%, and an mAP@50 of 92.2%, as well as a high F1-score for both object classes. The confusion matrix results also show a dominance of true positive and true negative values, indicating that the model is capable of classifying weapon objects accurately and consistently. In the detection testing stage using images that had been modified through various conditions, such as angle rotation, grayscale, blur, brightness, exposure, and noise addition, the YOLOv11 model was generally able to maintain stable detection performance. Changes in image conditions such as rotation, grayscale, brightness, and exposure did not have a significant effect on detection results, with confidence values mostly in the good to very good category. However, in image conditions with 50% noise added, there was a decrease in detection performance, especially for long gun objects, although the confidence values produced were still quite good. Testing based on image capture distance differences of up to 2 meters showed an effect on the detection confidence level, particularly for short gun objects, which experienced a decrease in confidence values in several images. Nevertheless, the YOLOv11 model was still able to detect all weapon objects in the test images with confidence values that remained in the good to very good category, demonstrating the model's good generalization ability against distance variations. Overall, the use of a large dataset consisting of approximately 11,969 images, supported by comprehensive data augmentation techniques, has proven to improve the performance and robustness of the YOLOv11 model against various image conditions. This study makes three main scientific contributions. First, this study provides an empirical evaluation demonstrating that YOLOv11 outperforms YOLOv8 in firearm detection tasks, achieving a precision of 91.3%, recall of 85.9%, mAP@50 of 92.2%, and mAP@50-95 of 78.6%, which are superior to the 84%, 77%, 84%, and 88% F1-score reported for YOLOv8 in previous studies. Second, this study systematically analyzes the robustness of YOLOv11 across seven diverse image conditions, providing empirical evidence of the model's stability and limitations under real-world scenarios. Third, this study demonstrates that YOLOv11, trained on a large and well-augmented dataset, holds strong potential as a reliable component for deployment in real-time public surveillance and security systems. Therefore, further research can focus on expanding testing scenario variations, such as extreme environmental conditions, more complex camera

angles, and real-time detection system integration to support implementation in real-world surveillance and security systems.

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