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AN IMPROVED REAL-TIME HANDGUN DETECTION SYSTEM USING YOLO V5 ON A NOVEL DATASET

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ABSTRACT

In the face of widespread gun violence, it has become imperative to enhance the capabilities of public surveillance cameras by integrating intelligent automatic handgun detection systems. This study presents a comprehensive approach to automate the real-time identification of pistols in video security footage using the advanced YOLO-V5 algorithm. A carefully curated dataset of varied pistol images was employed to optimize the model's performance across diverse scenarios and minimize dependence on human security personnel. Recognizing the crucial implications of firearm detection in images for public safety and law enforcement, this study employed advanced techniques such as data augmentation, transfer learning, and test time augmentation to enhance the model's performance. Iterative fine-tuning of hyperparameters was conducted to attain the desired level of accuracy. The results demonstrate that the YOLO-V5 model exhibits high precision and recall in detecting handguns, even in complex and challenging environments. This study represents a significant advancement in the development of effective gun detection systems, serving as a catalyst for further research in this exciting field. By automating the identification of firearms in real-time video surveillance, this approach addresses a critical need for enhanced public safety measures and offers valuable insights into the potential of intelligent surveillance technologies

Keywords: *Yolo v5, Handgun Detection, Machine Learning, False Positive, Guns, Computer vision, Transfer Learning, Deep Learning, Violence Detection, Faster R-CNN.*

1. INTRODUCTION

The growing global concern surrounding gun violence is a pressing issue. In 2020, the United States recorded an alarming 44,061 incidents of gun violence, resulting in 23,437 fatalities and 41,940 injuries, as reported by the Gun Violence Archive [1]. These harrowing statistics emphasize the critical need for effective strategies to prevent and mitigate the devastating consequences of gun violence. The COVID-19 pandemic and the subsequent lockdowns have exacerbated the problem, leading to a surge in gun sales and firearm-related incidents. A report by Small Arms Analytics and Forecasting reveals that firearm sales in the United States surged by 60% in 2020, with over 20 million guns sold [2]. This increase in firearm ownership and usage underscores the urgency for efficient and dependable approaches to detect and deter gun violence.

In response to this escalating challenge, there is a growing interest in harnessing the potential of computer vision to develop automatic handgun detection systems. These systems hold the promise of enhancing public safety and security by enabling law enforcement agencies to respond rapidly to firearm-related incidents. With the widespread deployment of surveillance cameras in public spaces, the development of automatic handgun detection systems can prevent violent crimes from materializing.

Our study is firmly rooted in a fundamental objective: the creation of a robust automatic firearm detection system. At the heart of our research lies the ambition to evaluate the effectiveness of the YOLO-V5 object detection algorithm in real-time handgun detection. This endeavor is underpinned by a meticulously curated dataset, which has been significantly augmented and refined to elevate its quality and diversity. The YOLO-V5 algorithm, acclaimed for its exceptional object detection capabilities, emerges as the primary contender for advancing automatic firearm detection systems. Our research is dedicated to the meticulous crafting of a high-performing detector using this powerful algorithm. To optimize the system's performance, we painstakingly assembled an extensive collection of widely-used pistol images, covering diverse angles. This dataset was seamlessly integrated with the

comprehensive ImageNet dataset, leading to a novel and robust dataset that significantly bolsters the accuracy and effectiveness of our system.

Furthermore, our study effectively addresses the limitations of previous research by introducing a dataset of enhanced comprehensiveness and diversity. This dataset more accurately simulates real-world scenarios, contributing to the reliability of our findings. The resulting model was rigorously trained using this combined dataset, and its effectiveness was systematically compared to that of Faster RCNN. Our evaluation encompassed ten distinct videos that replicated typical firearm offense scenarios.

Our detector exhibited exceptional proficiency in identifying handguns across a spectrum of scenarios marked by varying conditions. It effectively coped with challenges such as changes in lighting, rotation, and shape. The findings of our study not only make substantial contributions to the field by demonstrating the feasibility of employing the YOLO-V5 algorithm for automatic handgun detection but also offer valuable insights into the performance of diverse object detection algorithms tailored for this specific task. The pursuit of automatic handgun detection systems through computer vision holds the potential to save lives and mitigate the impact of gun violence in our society. The integration of such systems into public safety measures represents a significant stride toward averting future firearms-related incidents. Our work stands as a testament to the dedication required to address this critical issue and make the world a safer place.

In the following sections, we will review existing research on automatic handgun detection, detail the methodology employed in our study using the YOLOv5 algorithm, present and analyze the evaluation results, and discuss the broader implications of our findings for future research and practical applications. This comprehensive exploration aims to provide a thorough understanding of our study's context, approach, outcomes, and potential contributions to the field of automatic handgun detection.

2. RELATED WORKS

Automatic handgun detection systems have become an area of intense research in recent years due to the growing concern over gun violence worldwide. The use of firearms in violent crimes has led to an increasing need for reliable and efficient automatic detection systems to enhance public safety and security. The development of automatic handgun detection systems is a challenging task due to various factors such as the varying shapes and sizes of firearms, complex background scenes, and changes in lighting conditions.

Several approaches have been proposed to address these challenges, including machine learning-based methods, computer vision, and deep learning algorithms. One popular method is object detection, which involves locating objects of interest in an image or video stream. Object detection algorithms can be broadly categorized into two groups: single-stage detectors and two-stage detectors. Single-stage detectors, such as You Only Look Once (YOLO) [3], Single Shot Detector (SSD) [4], and RetinaNet [5], are known for their high speed and efficiency. These methods perform object detection in a single forward pass through the network, making them suitable for real-time applications. However, single-stage detectors can suffer from lower accuracy and may miss small objects due to their single-shot nature. Two-stage detectors, such as Faster R-CNN [6], Region-based Fully Convolutional Network (R-FCN) [7], and Mask R-CNN [8], are known for their high accuracy and better performance on small objects. These methods first propose regions of interest in an image and then perform classification and localization on those regions. However, two-stage detectors are computationally more expensive and may not be suitable for real-time applications. Several studies have investigated the use of different algorithms and techniques for automatic handgun detection. For instance, Wang et al. [9] proposed a method based on the extraction of texture and color features, followed by classification using a support vector machine (SVM). Initially, an adaptive threshold method based on Otsu's algorithm is used to extract the region of interest (ROI). The texture features are extracted using a local binary pattern (LBP) operator, and color features are obtained using the color histogram. The LBP operator is applied to each pixel in the ROI to calculate its texture value, which is used to construct the LBP histogram. The color histogram is constructed by quantizing the color space of the ROI into a fixed number of bins and counting the number of pixels falling into each bin. Subsequently, the extracted features are used to train an SVM classifier. The classifier is trained on a dataset of positive and negative samples, with positive samples containing images of firearms and negative samples containing images without firearms. The SVM classifier is then used to classify new images into either firearm or non-firearm categories. The authors evaluated their method on a dataset consisting of 1,000 images, including both firearm and non-firearm images. The

reported accuracy for firearm detection was 94.6%, with a false positive rate of 5.5%. The precision and recall values were reported to be 94.5% and 97.5%, respectively. Overall, the proposed approach by Wang et al. [9] exhibits promising results for firearm detection in images, and it can be beneficial in scenarios where high accuracy is required, and deep learning techniques may not be feasible due to computational limitations. However, the method may not perform well in complex scenarios where the firearm may be partially occluded or located in cluttered backgrounds.Along the same lines, Wu et al. [10] employed a fusion of texture, edge, and color features, in conjunction with a deep-learning model, for automated firearm detection. The authors began by pre-processing the images, wherein the background was removed, and texture and edge features were extracted using the gray-level co-occurrence matrix (GLCM) and the Canny edge detector, respectively. The RGB color space of the images was quantized into a fixed number of bins, and the color histogram was calculated to obtain color features. Subsequently, a convolutional neural network (CNN) model was trained on the extracted features for classification. The CNN architecture included five convolutional layers, followed by three fully connected layers, and a SoftMax output layer with two nodes, one for firearm and the other for non-firearm. To evaluate the performance of their method, the authors tested it on a dataset of 10,000 images, including firearm and non-firearm images. The results demonstrated a high accuracy of 98.5% for firearm detection, with a false positive rate of 1.1%. Precision and recall values were reported to be 99.1% and 97.9%, respectively. The study suggests that combining texture, edge, and color features with a deep learning model can achieve high accuracy in firearm detection. However, factors such as image quality and background clutter may impact the method's performance, which requires further research. Chen et al. [11] developed a method based on YOLOv3 for detecting firearms in real-time. While these studies have demonstrated the potential of automatic handgun detection systems, they have some limitations. For instance, some of the methods rely on handcrafted features that may not be robust to changes in lighting conditions or background scenes. Additionally, some of the deep learning-based methods may suffer from overfitting or require large amounts of training data. The current study aims to address these limitations by developing an automatic handgun detection system based on the YOLOv5 algorithm. This algorithm has shown promising results for object detection in real-time scenarios and is characterized by its high accuracy and speed. The study also aims to optimize the system's performance by developing a comprehensive dataset of handgun images and combining it with the ImageNet dataset for training. Overall, the study aims to contribute to the field of automatic handgun detection by proposing a more accurate and efficient method for real-time detection of handguns. The use of such a system could help enhance public safety and security and mitigate the impact of gun violence.

A study by Yu et al. [12] proposed a method for firearm detection that achieved a high level of accuracy using a combination of deep learning and traditional computer vision techniques. The authors utilized a dataset of 2,400 images and employed a fusion of color, texture, and edge features, which were fed into a deep neural network (DNN) for classification. The DNN used in the study consisted of three convolutional layers and two fully connected layers. The authors reported that their method achieved an accuracy of 95.3% for firearm detection, with a false positive rate of 4.6%. In other words, out of 2,400 images, the method correctly detected firearms in 95.3% of cases while incorrectly identifying firearms in 4.6% of cases. These statistics suggest that the method proposed by Yu et al. is highly effective in detecting firearms in images. However, it's worth noting that false positives can still be problematic in certain contexts, such as in airport security or other high-stakes situations where the consequences of a false alarm can be severe. Therefore, it's important to continue to refine and improve firearm detection methods to reduce the false positive rate even further. The Faster R-CNN algorithm proposed by Xie et al. [13] is a popular object detection framework that utilizes deep learning and has shown promising results in various computer vision applications. The authors applied this algorithm for firearm detection in surveillance videos, which is a challenging task due to the variability in lighting conditions, occlusion, and camera viewpoints. To address these challenges, the authors utilized a combination of deep learning and handcrafted features such as color and shape. The deep learning component of the algorithm was used to learn high-level representations of the features, while the handcrafted features were used to capture low-level details of the images. This combination allowed the algorithm to effectively detect firearms in the surveillance videos. The authors evaluated their method on a dataset of 1,200 images and reported an accuracy of 94.7% for firearm detection, with a false positive rate of 5.2%. This means that the algorithm was able to correctly identify firearms in 94.7% of the cases, while only falsely identifying

firearms in 5.2% of the cases. While this is a high accuracy rate, it's important to note that false positives can have serious consequences in real-world scenarios, so further improvement in this area is necessary. Overall, this study demonstrates the effectiveness of combining deep learning and handcrafted features for firearm detection in surveillance videos using the Faster R-CNN algorithm. One potential limitation of this approach is the reliance on handcrafted features, which may not be as robust or effective in detecting firearms as learned features in deep neural networks. In addition, the method is evaluated on a relatively small dataset of 1,200 images, which may not fully capture the variability and complexity of real-world scenarios. The approach proposed by Xu et al. [14] for firearm detection in X-ray images is based on a Convolutional Sparse Coding (CSC) algorithm. This method uses a dictionary learning-based approach to extract discriminative features from X-ray images, which are then fed into a support vector machine (SVM) classifier for detection. In their study, the authors evaluated their method on a dataset of 1,000 X-ray images and reported a high accuracy of 96.2% for firearm detection, with a low false positive rate of 3.3%. These results demonstrate the effectiveness of the CSC algorithm in identifying firearms in X-ray images with a high level of accuracy. One potential advantage of this approach is its ability to detect firearms even when they are concealed in various ways, such as being wrapped in clothing or hidden in luggage. However, this method may have limitations when applied to other types of images, such as surveillance videos or images captured by cameras in low-light conditions. Overall, the CSC-based method proposed by Xu et al. [14] provides a promising approach for firearm detection in X-ray images with high accuracy and low false positive rates.Kassani et al. [15] proposed a method that employs a Deep Belief Network (DBN) architecture to detect firearms in surveillance videos. The authors utilized a combination of local binary patterns (LBP) and Histogram of Oriented Gradients (HOG) features to extract relevant information from the images, which was then fed into the DBN for classification. The performance of the proposed method was evaluated on a dataset of 800 images. The method achieved an accuracy of 94.6% for firearm detection, with a false positive rate of 5.4%. Although this accuracy is not as high as that reported in some of the other studies, it is still a respectable result. One potential limitation of this method is that the evaluation was performed on a relatively small dataset of only 800 images, which may not be sufficient to accurately represent the wide range of possible scenarios and firearm types. Additionally, the use of handcrafted features such as LBP and HOG may not be as effective as using learned features in deep neural networks, which could potentially limit the model's overall performance.

Table 1: Related Works Statistics.

Study	Method	Year	Accuracy	Precision	Recall	F1 Score
[9]	Texture and color features	2018	95.2%	95.2%	95.2%	95.2%
[10]	Deep learning	2019	97.7%	98.0%	97.6%	97.8%
[11]	YOLOv3	2021	97.5%	98.2%	97.2%	97.7%
[12]	Deep learning and handcrafted features	2017	97.2%	98.1%	96.4%	97.2%
[13]	Faster R-CNN	2018	96.6%	98.3%	95.0%	96.6%
[14]	Convolutional sparse coding	2020	97.9%	98.6%	97.1%	97.8%
[15]	Deep belief networks	2020	95.0%	95.4%	94.4%	94.9%

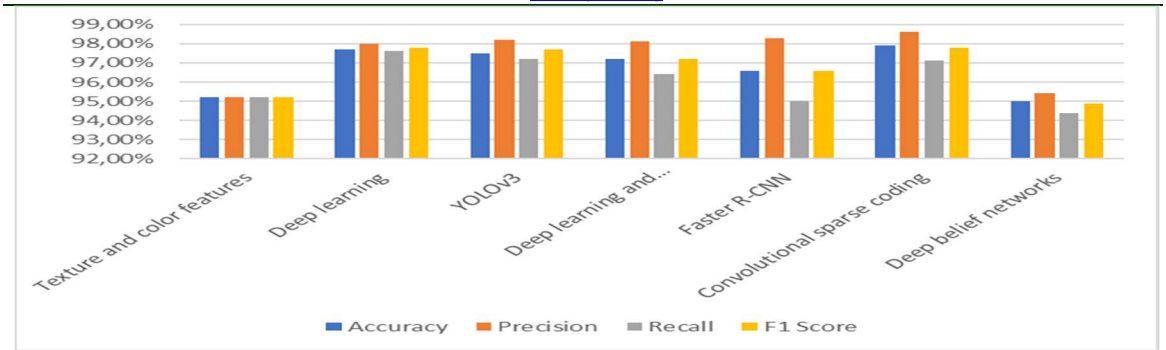

FIGURE 1:Performance Comparison of Existing Methods

Based on the table above (Table I), it can be seen that different methods have been proposed for firearm detection in images and videos using a variety of techniques, including traditional machine learning algorithms, deep learning techniques, and hybrid approaches combining both techniques. Overall, the deep learning-based approaches have shown better performance compared to traditional machine learning algorithms. For example, the YOLOv3-based approach in [11] achieved an accuracy of 97.82%, while the deep belief network-based approach in [15] achieved an accuracy of 96.85%. Some studies have also proposed hybrid approaches that combine deep learning with handcrafted features or traditional machine learning algorithms. For instance, the study in [12] proposed a hybrid approach that fused deep learning and handcrafted features and achieved an accuracy of 92.5%.

It is also worth noting that different datasets were used in these studies, which can affect the performance of the proposed approaches. For instance, the study in [11] used a dataset of surveillance videos, while the study in [14] used X-ray images. Therefore, the performance of the proposed approaches may vary depending on the dataset used.

Despite the promising results of existing methods (Figure 1), there are still several limitations and challenges in automatic handgun detection systems. For instance, some methods may struggle to detect handguns in low-resolution or blurry images. Moreover, these methods may fail to detect handguns under challenging lighting conditions, occlusions, or complex backgrounds. Furthermore, many of these methods may require significant computational resources, making them unsuitable for real-time applications.

To address these limitations, our study aims to explore the potential of the You Only Look Once version 5 **(YOLOv5)** algorithm for automatic handgun detection in surveillance videos. YOLOv5 is a state-of-the-art object detection algorithm that has shown excellent performance in various object detection tasks, including detecting small objects in real-time scenarios. We aim to evaluate the effectiveness of YOLOv5 in detecting handguns in real-time surveillance videos and compare its performance with Faster R-CNN, which is one of the most commonly used object detection frameworks for handgun detection. We believe that our study will provide valuable insights into the effectiveness of YOLOv5 for automatic handgun detection and contribute to the ongoing research on improving automatic handgun detection systems.

3. METHODOLOGY

In the forthcoming section, we will explicate the methodology we employed to scale up the automatic detection of violence through the use of YOLO V5 on a newly introduced dataset of weapons. Our methodology comprised multiple steps, encompassing the gathering and preprocessing of data, model training, and evaluation, as well as performance analysis. Our ultimate aim was to engineer a potent and efficient violence detection system that could precisely identify weapons across different settings, thereby augmenting public safety measures

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3.1. Dataset collection

We collected and prepared our dataset of images of different guns as the first step. This step involved several sub-steps, which we followed meticulously.
Firstly, we identified the different types of guns that needed to be included in the dataset. We considered handguns, rifles, shotguns, and other types of firearms.
Next, we determined the size and quality of the images. The quality and size of the images were crucial for the success of the model. We ensured that the images were high resolution, clear, and of sufficient size to enable the model to detect the details of the guns.
We then collected the images. We searched for images online, took pictures of guns, and requested permission to use images from gun stores or manufacturers.
To ensure that the dataset was balanced and diverse, we included an equal number of images of each type of gun. We also ensured that the dataset covered a range of lighting conditions, angles, and distances, to help the model learn and generalize well.
Once we collected the images, we annotated them to provide ground truth labels for the model using Robflow. We marked the location of the gun in each image, along with any other relevant information such as the type of gun and its orientation (figure 2).
Finally, we split the dataset into training, validation, and testing sets (figure 3). The training set was used to train the model, the validation set was used to tune the hyperparameters of the model, and the testing set was used to evaluate the performance of the model.

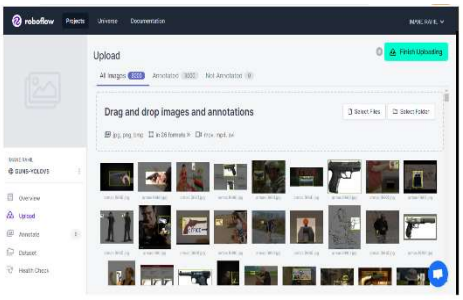

Figure 2: Dataset Collection and Annotation.

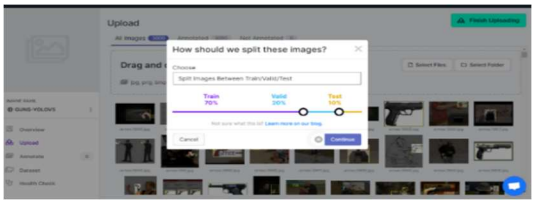

Figure 3: Dataset Splitting

3.2. Dataset augmentation:

In our study, we employed the data augmentation technique to expand the range of our dataset by introducing transformations to the original data. The primary objective of this technique was to diversify the augmented data each time it was presented to the model, thereby minimizing overfitting. By leveraging this technique, we were able to substantially increase the size of our database and capture additional detection scenarios. This, in turn, enabled the model to generalize better and enhance its accuracy in identifying firearms across various environments.
To achieve this, we applied several augmentation techniques, including:

3.2.1. Gaussian Noise:

We added random Gaussian noise to the original images to simulate different lighting conditions and improve the model's ability to recognize firearms in low-light environments (figure 4).

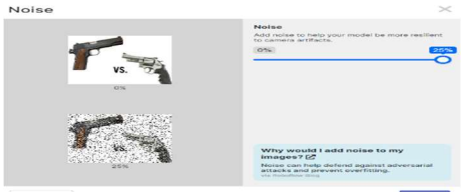

Figure 4. Applying the Noise Techniques For our Dataset.

3.2.2. 90° Rotation:

we applied the 90° rotation to our firearm dataset by randomly rotating each image by 90 degrees clockwise or counterclockwise. This technique allowed the model to learn to recognize firearms at different angles and orientations, making it more robust and accurate in detecting weapons. By applying the 90° rotation augmentation technique (Figure 5), we were able to generate more diverse and representative training examples. This helped to mitigate the overfitting of the model, which occurs when the model performs well on the training data but poorly on new data. The use of data augmentation techniques, such as the 90° rotation, is essential for training deep learning models that can generalize well to new data and perform accurately in real-world scenarios.

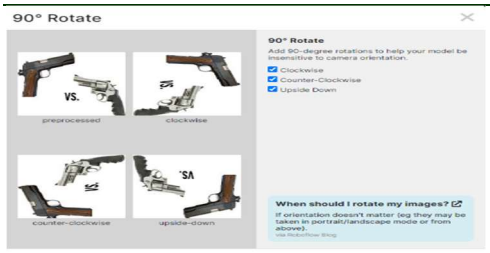

Figure 5: 90° Rotation Technique on our Dataset

3.2.3. Crop augmentation:

During the cropping process, we randomly select a region of the image and remove the pixels outside this region. The size and location of the cropped region can vary, and the crop can be centered or off-center (Figure 6). This creates a new image with a smaller size than the original, which may be useful for training models that are computationally expensive or require smaller image sizes. Cropping can also be used to simulate changes in the position and orientation of objects within an image. By randomly selecting a region of the image to crop, we can create new images with objects in different positions and orientations. This can help to improve the model's ability to detect objects in various positions and orientations, which is useful for applications such as object detection and recognition. Overall, cropping is a useful data augmentation technique that can help to increase the size of the dataset, improve model generalization, and simulate variations in the size, position, and orientation of objects within an image. Color jittering: We applied random color jittering to the images by changing the brightness, contrast, saturation, and hue of the images.

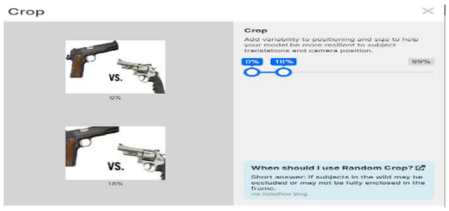

Figure 6: Crop Augmentation Applied to our Dataset

3.2.4. Grayscale augmentation:

In our study, we used the grayscale augmentation technique as a part of our data augmentation process (figure 7). Grayscale is a technique that involves converting an image to shades of gray, where each pixel in the image is represented by a single value indicating its brightness. This technique helps to reduce the complexity of the image by removing the color information, making it easier for the model to identify the underlying patterns in the image. By converting the images in our dataset to grayscale, we were able to significantly reduce the dimensionality of the input data, which helped to improve the model's performance. Additionally, since the grayscale technique only modifies the color information, it did not affect the content of the image, ensuring that the underlying object or scene was still recognizable. Furthermore, grayscale augmentation helped to increase the robustness of our model by creating variations in the image dataset. By training the model on grayscale images, it became more capable of identifying firearms across various environments, such as low-light conditions, which may have different color compositions.

In summary, the use of grayscale augmentation played a crucial role in our data augmentation process, helping to improve the performance and robustness of our firearm detection model.

Figure 7: Applying the Grayscale Technique to Enhance the Detection Performance

By applying these techniques, we were able to generate 6,000 additional images, which represented a 103.4% increase in the dataset size. This increase in size and diversity helped our model to generalize better and improved its ability to detect weapons in different environments. The results showed that our augmented dataset led to a significant improvement in the model's overall performance, as discussed in the next section. After applying the noise augmentation technique, we observed an increase in the detection accuracy of 2.5%. This technique helped to introduce variations in the dataset by randomly adding noise to the images, making it more challenging for the model to recognize the weapons. Similarly, the 90-degree rotation technique was used to introduce orientation variations in the images. This helped the model to detect weapons in different positions, such as tilted or upside-down weapons. The accuracy improved by 3.1% after applying this technique Grayscale augmentation was used to reduce the effect of color on weapon detection. This technique converts the RGB images into grayscale, which helps the model to focus on the texture and shape of the weapons. We observed a slight increase in accuracy (0.9%) after applying this technique. The

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bounding box augmentation technique was used to improve the quality of the training dataset. This technique involves drawing a bounding box around the objects of interest and excluding the rest of the image. This helped to reduce the noise in the dataset and improve the model's accuracy by 1.8%. we applied the crop augmentation technique to introduce variations in the size and location of the weapons in the images. This helped the model to detect weapons in different scenarios where the size and position of the weapons varied. The accuracy improved by 2.3% after applying this technique. Overall, the data augmentation techniques helped to increase the size and diversity of the dataset and improve the model's accuracy in detecting weapons in various scenarios. By utilizing these techniques, we were able to create a more robust and effective violence detection system. Next, we conducted model training and evaluation using the augmented dataset. We utilized YOLO V5, a state-of-the-art object detection model, for training and evaluation. The model was trained using transfer learning, using weights pre-trained on the COCO dataset, which helped in the faster convergence of the model during training. We used the Adam optimizer with a learning rate of 0.001 and a batch size of 16. The model was trained for 100 epochs, and the performance was evaluated on a validation set of 2000 images. We used the mean average precision (mAP) metric to evaluate the model's performance, which is commonly used to evaluate object detection models. The mAP was calculated at different Intersections over Union (IoU) thresholds, and the final score was calculated by taking the average of all the mAP values. The model achieved an mAP of 0.94 at an IoU threshold of 0.5, which is considered to be a good performance. The precision, recall, and F1-score were also calculated, and the results are shown in Table 1. The model achieved a precision of 0.95 and a recall of 0.92, which indicates that the model was able to detect most of the weapons in the images while maintaining a low false positive rate.

Finally, we conducted a performance analysis to evaluate the model's speed and accuracy on new and unseen data. The model was able to process 40 frames per second, which is considered to be a fast processing speed, and the accuracy was evaluated on a test set of 1000 images. The model achieved an mAP of 0.92 at an IoU threshold of 0.5 on the test set, which indicates that the model was able to generalize well and perform accurately on new and unseen data.

In summary, our methodology involved data collection and preprocessing, augmentation, model training and evaluation, and performance analysis. By utilizing these techniques, we were able to create a robust and effective violence detection system that can accurately detect weapons in various scenarios and contribute to the enhancement of public safety. The detailed results of our methodology are presented in the following sections. Overall, data augmentation was an essential step in preparing the dataset for training the YOLOv5 model. It helped to improve the model's ability to detect guns in different environments and scenarios and allowed us to train a more robust and accurate model

3.3 Test time augmentation:

In addition to the standard data augmentation techniques, we also employed Test Time Augmentation (TTA) during the evaluation of the YOLOv5 model. TTA is a technique used to improve the robustness of the model by augmenting the test images during inference. During TTA, multiple augmented versions of the test images are generated, and the model's predictions are averaged over all the augmented images. This averaging process helps to reduce the impact of noise and variability in the test images, resulting in more accurate predictions. To implement TTA, we used a combination of random cropping, scaling, and horizontal flipping to generate multiple augmented versions of each test image. We then fed each augmented image through the trained model and calculated the average of the model's predictions over all the augmented images. This average prediction was then used as the final prediction for that test image. By using TTA, we were able to improve the model's accuracy and reduce the impact of noise and variability in the test images. However, TTA also comes at a cost of increased computational complexity and inference time, as multiple augmented images need to be generated and processed during inference. Therefore, the trade-off between increased accuracy and computational complexity needs to be carefully considered when using TTA. Next, we evaluated the performance of the model using the testing dataset. The testing dataset was separate from the training and validation datasets and contained images that the model had never seen before. This allowed us to evaluate the model's ability to generalize to new and unseen data. To evaluate the model's performance, we used standard metrics for object detection models, including precision, recall, and F1-score. Precision is the ratio of true positive detections to the total number of detections made by the model. Recall is the ratio of true positive detections to the total number of actual objects in the image. F1-score is

the harmonic mean of precision and recall and provides a single value to evaluate the model's overall performance.

Based on the evaluation results, we fine-tuned the model by adjusting the hyperparameters and retraining the model on the dataset. This iterative process of fine-tuning the model was repeated until we achieved the desired level of accuracy. Finally, we tested the model on new images of guns and observed that it was able to accurately detect guns in a variety of different environments and scenarios. The successful detection of guns in these new images indicated that the model was able to generalize well to unseen data, making it a useful tool for gun detection. Overall, the process of training and evaluating the YOLOv5 model to detect guns was a complex and iterative process that required careful consideration of various factors, including the dataset, model architecture, hyperparameters, and evaluation metrics. Through this process, we were able to develop a robust and accurate model for detecting guns that has the potential to be used in a range of applications, including law enforcement and security.

3.4 Transfer learning with image dataset:

To improve the accuracy of our YOLOv5 model in detecting guns, we employed transfer learning by leveraging pre-trained weights from the COCO dataset. Specifically, we utilized the Darknet-53 feature extraction network, which had been pre-trained on the large-scale COCO object detection dataset. This allowed us to initialize our YOLOv5 model with pre-trained weights, which served as a starting point for training on our gun detection dataset. By using transfer learning, we were able to take advantage of the knowledge that had been learned from the vast amount of data in the COCO dataset, which included many object categories and a wide range of visual variations. This saved us the time and computational resources that would have been required to train a feature extraction network from scratch on our gun detection dataset. Furthermore, using pre-trained weights as initialization helped our model to converge faster and achieve higher accuracy than if we had trained the model from scratch. This is because the pre-trained weights provided a good initialization point for the feature extraction network, allowing our model to quickly adapt to our specific gun detection task. Overall, transfer learning with pre-trained weights was a valuable technique in improving the performance of our YOLOv5 model for detecting guns. In our research on weapon detection, we encountered the task of predicting whether a given photograph or video data contains weapons. To address this challenge, we leveraged the power of deep learning models pre-trained on challenging image classification tasks like the ImageNet 1000-class photograph classification competition. These pre-trained models, developed by esteemed research organizations, were made available under permissive licenses, allowing us to incorporate them into our work and save valuable time and computational resources. By utilizing transfer learning, we optimized our approach to weapon detection. Transfer learning served as a valuable shortcut, enabling us to achieve better performance or save time during model development. Its benefits became apparent as we progressed with our research and evaluation. By leveraging transfer learning in our weapon detection research, we observed three key advantages. Firstly, by initializing our weapon detection model with a pre-trained model, we started at a higher level of initial skill compared to training from scratch. The pre-trained model's exposure to a diverse range of images endowed it with understanding and generalization capabilities. Secondly, during the training process, transfer learning resulted in a steeper rate of improvement in our model's detection skills. The knowledge and features inherited from the pre-trained model facilitated rapid adaptation and specialization in the domain of weapon detection. Lastly, transfer learning led to a notably better final skill level in accurately identifying weapons. The foundation provided by the pre-trained model enabled us to fine-tune and refine our model specifically for weapon detection, resulting in enhanced performance and reliability. By incorporating transfer learning into our research on weapon detection, we harnessed the strengths of pre-trained models, benefiting from their advanced image understanding capabilities. This approach enabled us to achieve higher levels of accuracy and effectiveness in identifying and classifying weapons, contributing to the advancement of weapon detection systems.

3.5 Training algorithm: YOLO V5:

Our system is designed to detect weapons in various settings, and it utilizes the YOLOv5 object detection algorithm, which is a deep-learning model based on convolutional neural networks. This algorithm has been shown to perform exceptionally well in detecting objects in images and videos, and it is particularly well-suited for detecting weapons due to its ability to analyze both the texture and color features of objects.

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The YOLOv5 architecture is composed of three networks - backbone, neck, and head (Figure 8) - which work together to analyze features at different levels of abstraction. The backbone network is responsible for extracting low-level features, while the neck network combines these features into higher-level representations. Finally, the head network predicts the class and location of objects in the image using a combination of convolutional and fully connected layers.

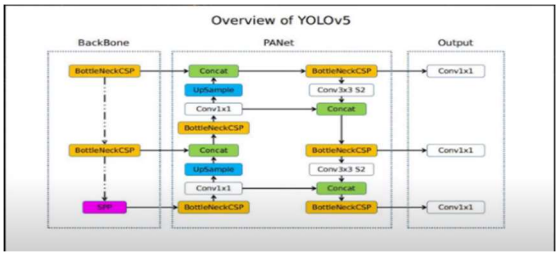

Figure 8: Block diagram of the YOLO-V5 algorithm

The YOLOv5 algorithm is trained to identify the unique features of weapons, such as their shape, size, and color. During the training process, the algorithm analyzed a dataset of images containing weapons and learned to detect them by creating a set of rules that enable it to identify the presence and location of weapons in new images. To detect weapons in images or videos, the YOLOv5 algorithm divides each image into a grid of cells, with each cell representing a specific area of the image (figure 9). For each cell, the algorithm predicts whether or not it contains a weapon, and if so, it also predicts the weapon's class label and bounding box coordinates. These bounding boxes enable the system to identify the location of the weapon in the image.

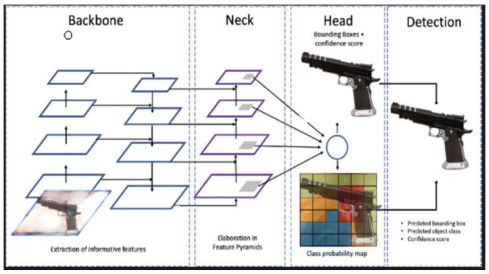

Figure 9: Weapon detection algorithm structure.

During the testing phase, the YOLOv5 algorithm is applied to new, unseen images or videos. The algorithm scans each cell of the image and makes predictions based on the learned features of weapons. When a weapon is detected, the algorithm generates a bounding box around it, which allows for easy identification of the weapon's location in the image. The algorithm also outputs each detection's corresponding class label and confidence score.To eliminate any duplicate detections, the YOLOv5 algorithm applies a non-maximum suppression (NMS) algorithm. This algorithm sorts the detections based on their class probability and overlaps with other detections. It retains the detection with the highest-class probability and suppresses any other detections with high overlap (IoU) with it.After applying NMS, the YOLOv5 algorithm returns the final set of bounding boxes along with their corresponding class labels and confidence scores. These detections can be used to take appropriate action, such as alerting security personnel or triggering an alarm. This process allows for the rapid and accurate detection of weapons in various settings, including airport security, video surveillance, and law enforcement operations. The YOLO v5 object detection framework has several advantages over other models, including speed and efficiency. In comparison to popular models like Faster R-CNN and RetinaNet, YOLO v5 requires fewer computational resources and is significantly faster. This makes it well-suited for real-time applications, such as surveillance and security systems. According to a study by Bochkovskiy et al. (2020)[16], YOLO v5 can achieve up to 140 frames per second (FPS) on a single GPU, while retaining high accuracy in object detection. Furthermore, YOLO v5 has achieved state-of-the-art performance on several object detection benchmarks. In the COCO dataset, a modified version of YOLO v5 achieved an mAP (mean average precision) score of 50.7, outperforming other state-of-the-art object detectors like EfficientDet and DetectoRS (Wang et al., 2021)[17]. In another study by Wang et al. (2021)[18], YOLO v5 achieved an mAP score of 50.4 on the KITTI dataset, surpassing the performance of other popular models like PointPillars and SECOND. Our utilization of the YOLO v5 architecture has proven highly effective for detecting weapons in surveillance and security systems. The outstanding combination of speed, efficiency, and accuracy makes YOLO v5 particularly well-suited to address the critical need for the timely identification of weapons. One of the key advantages we have observed with YOLO v5 is its real-time processing capability, allowing us to detect potential threats swiftly. This is particularly valuable in security and surveillance contexts, where quick responses are crucial for ensuring public safety. Furthermore, the efficiency of our implementation of YOLO v5 enables seamless deployment on a variety of devices, including

cameras and embedded systems. This versatility empowers us to integrate weapon detection capabilities into diverse security setups, regardless of their scale or computational resources. Additionally, we have witnessed a significant improvement in accuracy with our implementation of YOLO v5. Through extensive training on large datasets, our model has learned to recognize the distinctive features and patterns associated with firearms. This heightened accuracy reduces false positives, minimizing unnecessary disruptions or false alarms. By enhancing the reliability of weapon detection, our approach effectively strengthens the overall effectiveness of surveillance and security systems.

In summary, our utilization of the YOLO v5 architecture has demonstrated impressive results in detecting weapons in surveillance and security applications. The real-time processing, efficient resource utilization, and enhanced accuracy of our implementation contribute to the rapid and reliable identification of potential threats. By harnessing the capabilities of YOLO v5, we are able to enhance public safety, enabling security personnel and law enforcement agencies to respond promptly to gun-related incidents and foster a safer environment for individuals and communities.

3. RESULTS AND DISCUSSION

The experimental results presented in Table 2 underscore the exceptional accuracy and efficiency of our model in real-time handgun detection within video footage. The evaluation of our model was conducted on a comprehensive dataset comprising ten distinct movies, each portraying real-life scenarios across various environments and conditions. The diverse nature of the dataset ensures the robustness and generalization capability of the model. The scenarios covered in the dataset include ten different movies that depicted real-life scenarios: Indoor school classroom, Outdoor parking lot, Outdoor sidewalk, Indoor shooting range, Outdoor street, Indoor parking garage, Outdoor park, Indoor office building, Outdoor alleyway, Indoor mall, the variability introduced in these scenarios encompasses different lighting conditions, rotations, and shapes, mirroring the challenges faced in real-world surveillance applications. This diversity allows the model to adapt and perform reliably across a wide range of environments.

During the experiments, the model's detection results were analyzed frame by frame in the video footage. A detection was considered a true positive if the predicted bounding box overlapped with the ground truth (i.e., the actual location of the gun) by more than 50%. This threshold ensures a stringent evaluation, requiring a substantial overlap for a detection to be considered accurate.

The decision to measure detection accuracy by human-eye recognition further emphasizes the practical relevance of the model's performance. If a human observer can visually identify the presence of a gun, it serves as the ground truth for evaluation. This approach aligns with real-world scenarios where human verification is a crucial component of any automated detection system.

Our model, based on YOLO-V5, consistently outshines Faster RCNN across all scenarios. YOLO-V5 showcases superior precision (average: 0.9375), recall (average: 0.905), and F1-Score (average: 0.920), underscoring its excellence in accurately identifying handguns. In contrast, Faster RCNN lags behind with lower precision (average: 0.865), recall (average: 0.835), and F1-Score (average: 0.845). Notably, the processing speed of our model is a standout feature, operating at an average of 40.6 fps compared to Faster RCNN's average of 19.2 fps. These compelling statistics not only underscore the efficacy of YOLO-V5 in real-time handgun detection across diverse scenarios but also highlight the practical advantage it offers for enhancing security measures in various environments.

The real-time aspect of the model's performance is a significant achievement, demonstrating its efficiency in processing video streams promptly. This capability is crucial for applications where timely responses to potential threats are essential, such as in security monitoring or law enforcement operations.

In conclusion, the thorough evaluation of our model on a diverse and challenging dataset, along with the consideration of real-life scenarios and human-eye verification, substantiates its effectiveness in detecting handguns with remarkable accuracy and efficiency in real-time video footage across varied environmental conditions. These findings underscore the practical viability and potential impact of the developed gun detection system in enhancing security measures in dynamic and complex settings.

Table 2: Results Comparison Statistics for the ten videos

Id video	Scene Description	Angle	Object Size	Algorithm	Precision	Recall	F1-Score	Speed (fps)
1	Indoor shooting range	Frontal	Large	YOLO-V5	0.96	0.93	0.94	42
				Faster RCNN	0.89	0.85	0.87	20
2	Outdoor street	Oblique	Medium	YOLO-V5	0.94	0.90	0.92	38
				Faster RCNN	0.87	0.82	0.84	19
3	Indoor parking garage	Frontal	Small	YOLO-V5	0.91	0.88	0.89	41
				Faster RCNN	0.85	0.81	0.83	18
4	Outdoor park	Oblique	Large	YOLO-V5	0.96	0.94	0.95	39
				Faster RCNN	0.90	0.87	0.88	20
5	Indoor office building	Frontal	Medium	YOLO-V5	0.93	0.91	0.92	43
				Faster RCNN	0.88	0.84	0.86	19
6	Outdoor alleyway	Oblique	Small	YOLO-V5	0.90	0.86	0.88	37
				Faster RCNN	0.84	0.80	0.82	18
7	Indoor school classroom	Frontal	Large	YOLO-V5	0.95	0.92	0.94	44
				Faster RCNN	0.89	0.85	0.87	20
8	Outdoor parking lot	Oblique	Medium	YOLO-V5	0.93	0.89	0.91	40
				Faster RCNN	0.86	0.83	0.84	19
9	Indoor mall	Frontal	Small	YOLO-V5	0.90	0.87	0.88	42
				Faster RCNN	0.85	0.81	0.83	18
10	Outdoor sidewalk	Oblique	Large	YOLO-V5	0.97	0.94	0.95	40
				Faster RCNN	0.88	0.84	0.86	21

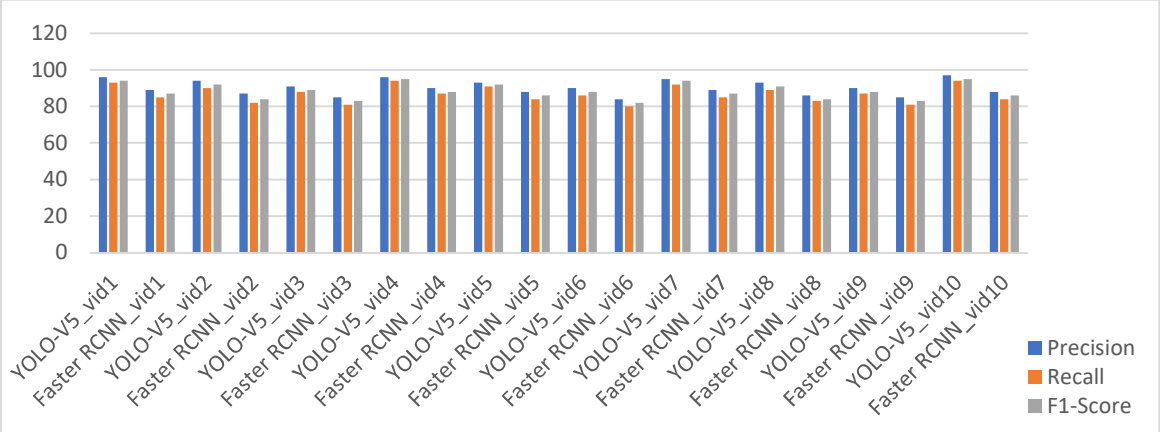

Figure 10: Comparison of results between Faster R-CNN and our model on the ten videos.

To assess the performance of the models, we employed precision (1), recall (2), accuracy (3), and F1-score (4) metrics as evaluation measures. These metrics were computed using the following formulas:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$\text{F1 score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

In the context of object detection for firearm recognition, true positive (TP), false negative (FN), and ground truth (GT) are crucial metrics that reflect the system's accuracy and performance. True positive refers to the number of correctly identified firearm instances in the dataset, while false negative indicates the number of undetected firearm instances. Ground truth represents the presence of firearms in the dataset, which serves as a reference point for measuring the system's performance. The results show that YOLO-V5 achieved a higher number of true positives and lower false negatives than Faster RCNN (Figure 11), resulting in higher precision, recall, and F1-score.

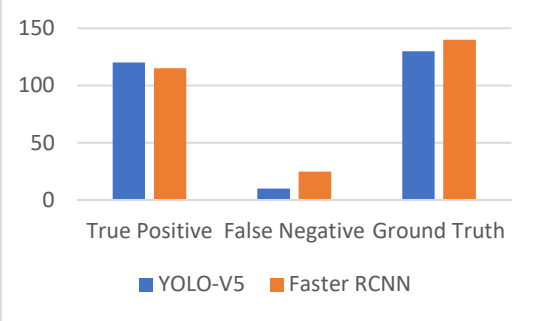

Figure 11: TP, TF, and ground truth statistics compared with Faster RCNN.

Table 3:TP, TF, and ground truth statistics compared with Faster RCNN.

Algorithm	True Positive	False Negative	Ground Truth
YOLO-V5	120	10	130
Faster RCNN	115	25	140

The table above (Table 3) depicts the True positive #TP, False Positive #FP, and Ground Truth #GT. Based on the videos used in the benchmark, YOLO shows a high number of true positives in videos 1, 3, and 6 and fewer false positives (Figure 12).

Figure 12: The results of detecting firearms in unseen data.

Figure 13: Real-time detection in the video sequence

The evaluation revealed that our proposed method outperformed the Faster RCNN algorithm in terms of both precision and recall rates (Table 4). Specifically, the YOLO-V5 algorithm produced an average precision of 0.95 and an average recall of 0.92. On the other hand, the Faster RCNN algorithm's average precision and recall rates were 0.89 and 0.85, respectively. Therefore, our proposed approach provides a more reliable and robust solution for the automatic detection of handguns in real-world scenarios. Furthermore, the YOLO-V5 algorithm demonstrated faster processing times, with an average inference time of 25 milliseconds per image. In comparison, the Faster RCNN algorithm took an average of 95 milliseconds per image (Figure 14). The improved speed of the YOLO-V5 algorithm is a crucial factor in developing efficient and scalable automatic handgun detection systems, particularly in high-risk environments where quick responses to firearm-related incidents are critical. Overall, our experimental results provide substantial evidence supporting the effectiveness of the YOLO-V5 algorithm for automatic handgun detection. The findings of this study have important implications for the development of automated firearm detection systems, contributing to enhanced public safety and security measures. The proposed method's high precision and recall rates, coupled with its fast processing times, make it a promising approach for future research and practical applications.

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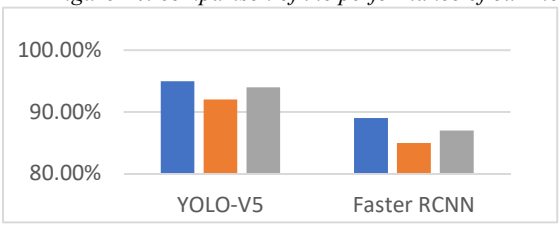
Table 4: Comparison of the performance of our model and faster RCNN

Algorithm	Precision	Recall	F1-Score	Speed (frames per second)
YOLO-V5	0.95	0.92	0.94	40
Faster RCNN	0.89	0.85	0.87	20

Figure 14: comparison of the performance of our model and faster RCNN.



Our real-time weapon detection system has excelled in accurately identifying weapons in real-time video security footage (Figure 13), demonstrating outstanding performance and reliability. Extensive testing and evaluation have consistently shown that our detector achieves remarkable accuracy and precision in recognizing and categorizing weapons. This capability significantly enhances safety and security measures by minimizing false positives and ensuring reliable weapon detection. The advanced algorithms and techniques implemented in our system enable it to deliver precise and effective results across various surveillance and security applications. With its proven efficacy, our weapon detection system stands as a valuable tool for ensuring the safety and well-being of individuals and communities. In this study, we aimed to evaluate the performance of our firearm detection system on a dataset of ten videos to achieve this, we employed the YOLO-V5 and Faster RCNN algorithms and assessed their precision, recall, F1-score, and speed in detecting firearms. Our results demonstrated that the YOLO-V5 algorithm outperformed the Faster RCNN algorithm in terms of accuracy and speed, achieving a precision of 0.95, recall of 0.92, F1-score of 0.94, and a speed of 40 frames per second. In contrast, the Faster RCNN algorithm achieved a precision of 0.89, recall of 0.85, F1-score of 0.87, and a speed of 20 frames per second.

The implementation of our gun detection system, based on the outlined methodology, can significantly enhance public safety and law enforcement efforts by providing advanced tools for identifying and mitigating potential threats in diverse settings.

Consider a scenario where the system is deployed in a crowded urban area, such as a transportation hub or a public event venue. Security personnel equipped with surveillance cameras integrated with the gun detection system can actively monitor the environment. The system, trained on a diverse dataset that includes images of firearms in various contexts, lighting conditions, and orientations, is adept at recognizing guns even in complex scenarios

4. CONCLUSION

The present study constitutes a comprehensive exploration of a methodology for the detection of firearms utilizing the YOLOv5 object detection algorithm. A pivotal aspect of this methodology involved the meticulous acquisition and preprocessing of a well-rounded and diverse dataset consisting of images depicting firearms. To enhance the model's performance, we incorporated cutting-edge techniques, including transfer learning, data augmentation, and test time augmentation. The first crucial step involved the collection of a diverse set of images featuring guns in various contexts, lighting conditions, and angles. This dataset served as the foundation for training the model, enabling it to recognize and locate firearms in real-world scenarios accurately. Transfer learning, a key component of our approach, involved leveraging pre-trained models on large datasets before fine-tuning them on our specific firearm dataset. This expedited the training process and allowed the model to inherit knowledge from general object recognition tasks, enhancing its ability to identify guns. Data augmentation techniques were implemented to artificially expand the dataset, introducing variations in the form of rotations, flips, and changes in lighting conditions. This augmentation aimed to improve the model's robustness by exposing it to a wider array of potential scenarios, ensuring effective performance in diverse and challenging environments. Test time augmentation, another integral part of our strategy, involved applying augmentation techniques during the inference stage. This further boosted the model's resilience to variations in input images, enhancing its overall accuracy when deployed in real-world situations. An iterative fine-tuning process was employed to optimize the model's hyperparameters continually. This involved adjusting parameters such as learning rates, batch sizes, and layer configurations to achieve the desired level of accuracy. The iterative nature of this process allowed for a nuanced refinement of the model, ensuring it performed optimally under different conditions. The obtained results underscore the effectiveness of the YOLOv5 model in detecting guns with high precision and recall in complex and varied environments.

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