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Improving Handgun Detection: A Review and Proposal for Knowledge Graph Integration

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ABSTRACT

Gun violence is a significant social issue, and in order to successfully identify firearms, advanced surveillance systems must be developed. Even with the introduction of deep learning algorithms like YOLO [5] and Faster R-CNN [61], it is still challenging to de- tect hidden weapons due to dynamic backdrops, shifting illumination, and partial object visibility. Even while current methods achieve high accuracy under ideal settings, they suffer significantly in real-world scenarios such object occlusion. Current handgun de- tection techniques are examined in this paper, which also divides them into deep learning and traditional approaches and identifies their drawbacks. We suggest combining knowl- edge graphs to tackle occlusion issues and false negatives by employing contextual and semantic links. Experimental validation demonstrates substantial improvements in preci- sion (94.1%) and F1-score (92.6%) compared to standalone deep learning models, with a 59% reduction in false negatives for occluded objects. The purpose of this study is to stim- ulate additional developments in reliable and all-encompassing firearm detection systems for public safety.

Keywords: *Algorithms, CCTV, Deep Learning, Knowledge Graph, Handgun Detection, Object Detection, Review.*

1 Introduction

The need for efficient firearm detection systems is underscored by the increase in gun violence. Despite being widely used, CCTV surveillance is inefficient since it relies on human monitoring [2]. In controlled situations, deep learning algorithms such as YOLO [5][58] and Faster R-CNN [61] demonstrate great accuracy; but, in real-world scenarios, they face difficulties such occlusion, dynamic environments, and inadequate lighting [37][38]. Because of these restrictions, detection accuracy is decreased, especially for items that are partially visible or hidden.

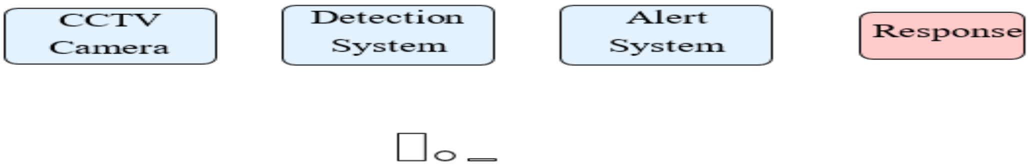

Figure 1: Automated Handgun Detection System Flow

To solve these problems, this paper suggests combining deep learning with knowledge graphs. Knowledge graphs can increase the robustness of handgun detection by utilizing con- textual linkages and semantic information, which will improve public safety and the depend- ability of surveillance systems [3]. The shortcomings of current handgun detection techniques are examined in detail, and the objective is to create a reliable, effective detection system that will support security and law enforcement organizations, promoting public safety and coopera- tive research. In the end, the study aims to spur advancements in automated handgun detection, a vital instrument in the fight against the escalating problem of gun violence in society.

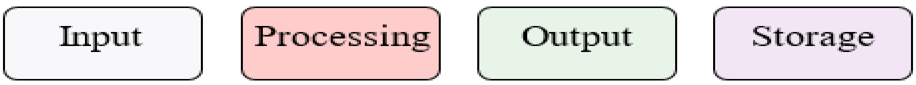

Figure 2: Model of Object Detection [3]

2 Literature Review

Over the past ten years, automated systems for handgun detection have undergone tremendous change, with different strategies providing differing levels of success [11][12]. This section examines the body of research, classifying the approaches into deep learning-based solutions and conventional approaches, and emphasizing their advantages, disadvantages, and areas in need of more research.

2.1 Algorithm Categorization for Handgun Detection

Handgun detection algorithms can be broadly categorized into two types: Non-Deep Learning Algorithms and Deep Learning Algorithms [13][14].

2.1.1 Non-Deep Learning Algorithms

Initially, algorithms are employed by same techniques such as color segmentation, interest point detection form analysis and mostly edge detection [17][18]. Of course, these algorithms are not perfect either. They are sensitive to image quality and viewing angles, thus they struggle with obstructions in the way of a clear view. It is very challenging for object detection due to the existence of noise and occlusion in images [12]. Furthermore, causing the corners of images and shapes that are occluded is also difficult for these non-deep learning algorithms to accurately pinpoint. In addition, segmenting an image is hard if the color of a target object and those surrounding it are alike to one another in that they cannot be identified clearly enough for them be separated.

2.1.2 Deep Learning Algorithms

Deep Learning Algorithms, in contrast use deep neural networks to execute their tasks [11][13]. These have been shown to outperform non-deep learning methods and more efficiently cope with a wider variety of image conditions [23][24]. It brings several benefits with it: CNN [32][33], YOLO [5][39][58], Faster R-CNN [61] and many other types of deep learning algo- rithms. One of the most important advantages is that they can remove the laborious job of doing manual feature engineering, e.g. find edges or corners. During training, these algorithms have the ability to dynamically learn and extract their features [5][14]. They need a lot of (labeled) data for training but the availability of labeled samples, helps them in detecting the objects well.

2.2 Handgun Detection Using Non-Deep Learning Algorithms

This part does not cover deep learning algorithms. Instead, these algorithms use image segmen- tation techniques such as shape-based edge detection [17][18]. Edge Detection: Edge detection is the process which used for finding boundaries between regions of image [18]. Another dif- ficulty is that it requires identifying edges by some edge detection method in advance then decreasing the data volume to make an image processing possible. Moreover, edge detection supports the process of highlighting objects in the image [18]. On the other hand, shape detec- tion are used to detect contours of objects in an image. This allowed it to recognize and extract shapes from an image where are as well carrying out other calibration quickly [19].

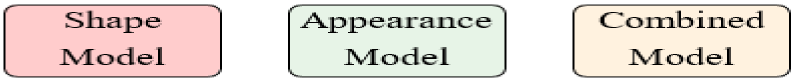

Figure 3: Model for shape detection using AAM [19][20]

2.2.1 Edge Detection

Edge detection is a technique used to identify boundaries between different regions within an image [18]. It involves applying specific edge detection methods to locate edges in advance, thereby reducing data volume and enabling efficient image processing. Furthermore, edge detection plays a crucial role in highlighting objects within an image, facilitating their recognition and analysis [18]. However, this method can face challenges in noisy environments or when image quality is low.

2.2.2 Shape Detection

Shape detection focuses on identifying and extracting the contours of objects within an image [19]. This approach allows for the recognition and segmentation of shapes, enabling quick calibration and further analysis [19]. While effective in controlled environments, shape detection can encounter difficulties in complex scenarios where objects are occluded or have similar shapes to their surroundings.

2.2.3 The Active Appearance Model (AAM)

Active Appearance Models (AAM) [20][28] is a computer vision technology applies a statisti- cal model to align objects shape and appearance in an image. This technique is exploited well in the field of face detection, medical image analysis and many more. It labels and locates the key landmarks in relation to the images that need learning/have been learnt for each image during training [20]. In order to build a shape detection model with AAM the steps shown in figures 2 and figure 3 could be pursued:

1. Annotate the images with key points or landmarks.
2. Represent the x-coordinates of these landmarks as a vector.
3. Capture the shape coordinates for modeling.
4. Normalize the shapes using Principal Component Analysis (PCA).

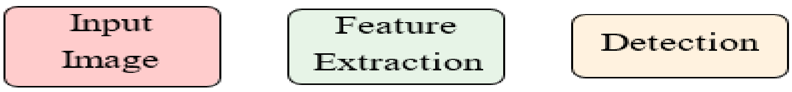

Figure 4: Firearm detection process [19][20][25][38][56]

Strengths and Challenges of AAM Active Appearance Model (AAM) [28] is an efficient tool in computer vision to explain and model the shape and appearance variations of objects [65]. The versatility of AAMs makes them adaptable and robust in many situations–from face recognition to medical imaging applications. By incorporating active contour methods and using statistical models, they can address the problems of lighting variations as well object bor- ders. Their use of various dimensionality reduction techniques helps streamlining computation and they excel in real-time video analysis or surveillance tracking. AAMs excel in tasks such as landmark detection and expression analysis with facial understanding. Finally, their genera- tive abilities that encourage data augmentation can be quite helpful [65]. But it is also worthy to note that they come with their own constraints. AAMs may perform poorly when there is occlusion, or the background of image has substantial complexity. Moreover, novel competing solution possibilities such as deep-learning certain applications, challenging AAMs in some scenarios.

2.2.4 Harris Corner Detector

The Harris Corner Detector [46][63][64][67] is a widely used algorithm in computer vision, initially developed as a corner detection method. Its primary purpose is to identify edges or key points in an image by analyzing the intensity and gradient of pixels. The Harris Corner Detector has been successfully applied in various tasks, including image registration, feature extraction, and object tracking [46][63][64][67].

Steps for Corner Detection Using Harris Corner Detector:

1. Convert the colored image to grayscale.
2. Compute the spatial derivative of the image.
3. Construct the tensor structure for each pixel.
4. Calculate the Harris response for each pixel.
5. Apply non-maximum suppression to retain only the most prominent corners.

Harris Corner Detector

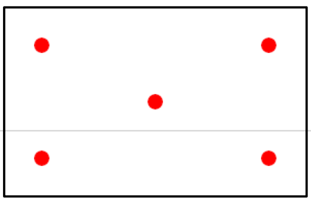

Figure 5: Harris Corner Detector [46][63][67]

Key Characteristics of Corners are points in an image whose local neighborhood exhibits high variance in all directions. These points are particularly significant because they remain relatively invariant to changes in viewpoint or lighting conditions, making them essential for robust feature detection and matching. In 1988, Chris Harris and Mike Stephens introduced the Harris Corner Detector [63], which has since become a cornerstone technique in computer vision.

Strengths and Challenges of the Harris Corner Detector The Harris Corner Detector [46][63][64][67] is a robust and efficient method for identifying corners in images, widely regarded as a powerful tool in feature detection. Its notable strengths include:

- Effectiveness: Provides reliable corner detection, which is critical for applications such as object detection, image matching, image registration, and image segmentation.
- Simplicity and Speed: The algorithm is computationally efficient and straightforward to implement, making it suitable for real-time applications.
- Versatility: Adapts well to a wide range of image processing tasks across diverse domains.

Figure 6: Image processing stages [14][15][29][30][42][44][53][54]

However, the Harris Corner Detector also has certain limitations that require attention during implementation:

- Sensitivity to Noise: The method is prone to false detections in noisy images, necessitating effective preprocessing to reduce noise.
- Dependence on Parameter Tuning: Requires prior knowledge of corner strength and careful parameter tuning to achieve optimal performance.
- Challenges with Complex Structures: Struggles to detect corners accurately in images with intricate or highly textured regions.

2.2.5 K-Means Clustering for Color-Based Segmentation

K-means is a method for clustering data points into several groups [12]. In this algorithm, each data point is assigned to the cluster with the closest mean, determining its membership within a specific subset. The algorithm's output comprises k subsets, representing the final number of clusters. The k-means algorithm is utilized for handgun identification to achieve color-based segmentation. This process helps eliminate any irrelevant colors in the image. Subsequently, the item is detected using the Harris corner detector. The accuracy of this approach has been demonstrated to be around 84.26 percent [12].

Strengths and Challenges of K-Means Clustering for Color-Based Segmentation K-Means clustering is a versatile and effective algorithm for color-based image segmentation. Its simplicity, speed, and ability to segment various images make it a popular choice among image-processing practitioners. However, it is essential to note that K-Means clustering is noise-sensitive and requires prior knowledge of the number of clusters in the image [17]. Additionally, it may be unable to handle complex image structures with multiple objects or objects of varying colors. Despite these limitations, K-Means clustering remains a valuable tool for color-based image segmentation when used appropriately.

2.3 Handgun Detection Using Deep Learning Algorithm

A deep neural network is a machine learning algorithm that consists of multiple layers, each comprising interconnected neurons serving as input points [23]. In this network, each neuron within a layer is connected to other neurons in the same layer through weighted connections, where real numbers represent these weights. The contribution of neurons in one layer to those in the subsequent layer is achieved by multiplying their values with the corresponding weights and adding the weighted sum to a bias value [24]. Subsequently, an activation function processes this sum, transforming the value and passing it to the next neuron in the network. This iterative process propagates the inputs through the entire network. Predictions are obtained by the network's third and final layer. An error function applies to the layer's output to determine the prediction's accuracy. If the error is substantial, the weights are changed, and the training cycle is carried out once more to reduce the error [24].

2.3.1 Neural Network with Convolutions

Convolutional Neural Networks (CNNs) [32][33][37] have significantly contributed to deep learning and have achieved outstanding results in several fields, including computer vision and natural language processing. In recent years, industry and academia have expressed great interest in response to this accomplishment [33]. However, current assessments sometimes fail to provide a thorough overview of the network and instead concentrate on how CNN might be applied in particular situations. As a result, several novel concepts that have emerged recently go unconsidered in these assessments [33].

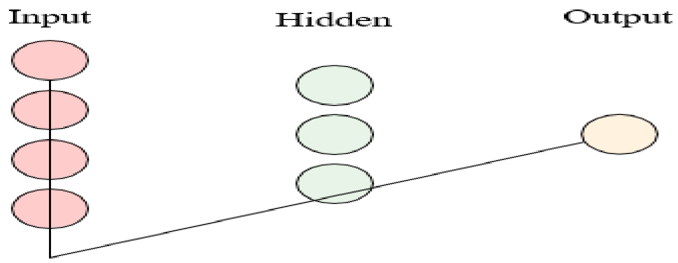

Figure 7: Simple Neural Network

CNN Processing Steps The image goes through several steps of processing in the convolu- tional neural network. The process begins by splitting the image into sections, also referred to as matrices. Each matrix is then sent through a max pooling layer and an activation function, among other unique layers. The max pooling layer is essential for down sampling the input and accentuating relevant features. After moving through these layers, the network generates an output, which is then compared to the initial class to determine the classification [32][33]. The network's accuracy is evaluated using error functions.

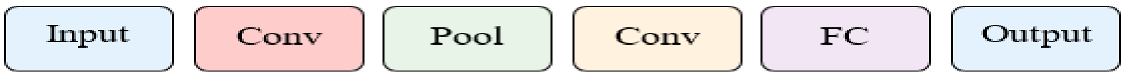

Figure 8: Architecture of CNN [1][7][8]

Importance of Activation Functions Activation functions are fundamental components in neural networks as they introduce non-linearity [34]. Within a neural network, inputs undergo linear transformations, and then an activation function processes them, yielding nonlinear counterparts. These non-linear point-wise activation functions significantly influence the overall performance of neural networks [34].

Introduction of the Serf Activation Function A novel activation function has been introduced, displaying desirable properties such as upper unsoundness, lower roundedness, non-monotonicity, and smoothness. Through extensive experimentation on diverse datasets and utilizing various state-of-the-art architectures for different tasks, the newly proposed activation function, Serf, demonstrates superior performance compared to both the baseline ReLU and other widely used activation functions like Swish, Mish, and GELU by a considerable margin [34].

Hyperparameter Fine-Tuning for Serf Additionally, by fine-tuning the hyperparameter of Serf through a hyperparameter search process, results can be improved [34].

Strengths and Challenges of CNNs Convolutional neural networks (CNNs) [32][33][37] have revolutionized the field of image recognition, achieving state-of-the-art performance in image classification, object detection, and image segmentation. Their translation and scale invariance, robustness to noise, and ability to learn from vast amounts of data make them highly effective for image-related tasks. However, their computational complexity, memory requirements, sensitivity to training data, and interpretability challenges demand careful consideration during implementation.

2.4 CONVOLUTIONAL NEURAL NETWORK FOR REGION-BASED DETECTION (R-CNN)

R-CNN, or Regions with CNN Features, is a powerful object detection model that employs CNNs to propose regions for localizing and segmenting objects [37]. This method utilizes selective search to identify potential bounding-box object regions, commonly called "regions of interest." Subsequently, it independently extracts feature from each region for classification purposes. In their study, the authors discuss the implications of their findings for the future development of handgun detection algorithms. They emphasize the importance of de- signing future algorithms to be more resilient to challenges like low resolution, poor lighting, and occlusion. The authors suggest that future algorithms should be evaluated using a more comprehensive benchmark, such as the CCTV-Gun benchmark [37].

Strengths and Challenges of R-CNN Convolutional Neural Network for Region-Based Detection (R-CNN) is a robust object detection algorithm that excels in accuracy, flexibility, robustness, scalability, and ease of use. However, its computational complexity, memory requirements, sensitivity to training data, and reliance on region proposals make it less suitable for real-time applications and require careful consideration during implementation.

2.5 FASTER R-CNN (REGION-BASED CONVOLUTIONAL NEURAL NETWORK)

A fully convolutional neural network called Faster R-CNN is made of two networks [38][61]. The first network generates region proposals, which the second uses to identify and categorize objects. When processing an image with Faster R-CNN, the following information is obtained:

a) A set of bounding boxes. b) Labels are given to each box. c) Probability scores match each box. Tensor representations of images have three dimensions: height, width, and depth. These tensors, or images, are sent through a convolutional model already trained until they get to an Intermediary layer, where they produce a feature map. The Region Proposal Network (RPN) is then given the feature map. The RPN uses these characteristics to suggest locations that might contain items. The RPN uses anchors—boxes of constant size with various ratios and sizes to forecast item placements to address the variable length problem. Once you have a list of likely things and their related locations, categorizing the objects becomes easy. The Region of Interest (Roi) pooling layer searches through CNN features and object boxes to identify characteristics closely associated with the objects. The item inside each box is subsequently classified using the R-CNN module, and any necessary changes to its coordinates are made.

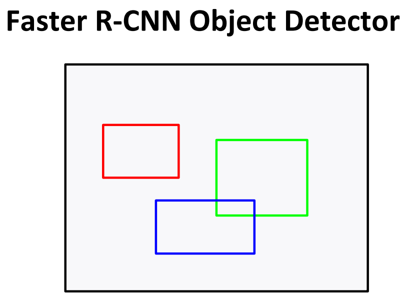

Figure 9: Faster RCNN Object Detector

Strength and Challenges of Faster R-CNN Faster R-CNN stands out as a powerful and versatile object detection algorithm, achieving real-time performance while maintaining high accuracy. Its strengths lie in its end-to-end training capability, scalability, and illumination and appearance variations robustness. However, Faster R-CNN's computational complexity, sensitivity to region proposals, and memory requirements make it crucial to carefully evaluate its suitability for specific applications.

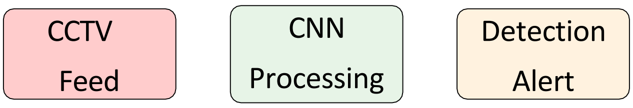

Figure 10: Real-time processing of handgun detection by CNN-based deep learning method [32][33][37][57][58]

2.6 YOLO (YOU ONLY LOOK ONCE)

Convolutional neural networks (CNNs) [32][33][37] are the foundation of the famous and in-fluential object identification method, YOLO [39][58], which stands for You Only Look Once. It can work both for detection in real time as well, with decent enough accuracy preserved over all regions [5][38][39][58][68][69][70][71][72][73][74]. A detection method is able to capture many multiple items within the same image, which cannot be received by any identification algorithms and does not recognize even a single object's placement.

Strength and Challenge of YOLO YOLO (You Only Look Once) [5][38][39][58] is a sim- ple and powerful object detection algorithm that can deliver real-time performance at the cost of more errors than region-based architectures due to lossy nature. Due to its ability of work- ing on large images/video streams, detecting objects over different sizes and shapes as well as various textures using one simple unified workflow. YOLO, however does not perform as well in terms of accuracy compared to some other algorithms and cannot handle localization, noise sensitivity or need for large training datasets. It may also have a limited computational window in terms of multi-scale object detection.

2.7 Knowledge Graphs in Computer Vision

Knowledge graphs, which offer organized representations of items and their relationships, have become an effective tool in many different fields. They have been used to improve object detection in computer vision by adding semantic and contextual information. Knowledge graphs allow models to make well-informed predictions about partially visible objects by connecting visual input with external knowledge, such as object properties, spatial relationships, and scene context. Knowledge graphs have been shown in recent research to be useful in increasing the detection accuracy of overlapping and obscured objects. For instance, it has been demonstrated that combining knowledge graphs with object detection pipelines improves performance when identifying items in challenging scenarios, such congested places and urban settings. This achievement encourages research into knowledge graphs as a solution to the occlusion issue in handgun detection.

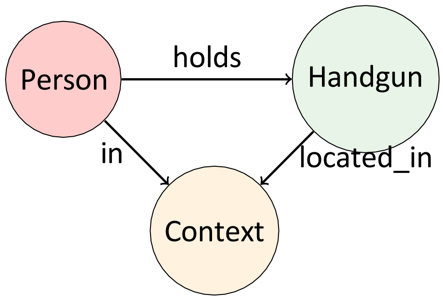

Figure 11: Knowledge Graph Representation for Handgun Detection

2.8 HYBRID ALGORITHMS FOR HANDGUN DETECTION

The data in Table 1 presents a comprehensive compilation of research papers investigating different algorithms for detecting handguns and knives[45][51][52][53][54][55][59][60][61][62][63][65][66][67]. Each entry in the table corresponds to a distinct research paper, providing details about the detection type, the algorithm employed, the dataset used, the maximum mean average precision (mAP) achieved, and the strengths and weaknesses associated with each algorithm.

Algorithm	Details

CenterNet	Strengths: Processing in real time. Effective in regulated environments. Limitations: Limited ability to reason about concealed elements; difficulty with substantially obscured things. Proposed Solution: To depict spatial relationships and de- duce properties of occluded objects, use knowledge graphs. Incorporate graph reasoning to increase precision.
Mask R-CNN	Strengths: High segmentation task accuracy. Sturdy bounding box predictions. Limitations: When objects are partially visible, performance suffers. Costly to compute for real-time tasks. Proposed Solution: Use semantic information from knowledge graphs to improve context comprehension. Reduce false negatives by employing inference based on graphs.
Faster R-CNN	Strengths: High accuracy in detecting items; effectively manages multiple items in still images. Limitations: Slower in dynamic situations. Poor handling of occlusion due to reliance on visual features. Proposed Solution: Use knowledge graphs to capture environmental factors influencing occlusions. Enhance temporal reasoning capabilities.
YOLO (v4/v5)	Strengths: Quick and instantaneous object detection. High efficiency and speed. Limitations: Struggles to detect heavily obscured objects accurately; reduced precision in complex scenes. Proposed Solution: Use knowledge graph-driven reasoning to predict occluded objects based on relationships and sur- rounding context.

SSD (Single Shot Detector)	Strengths: Performs well on smaller objects due to its sim- ple architecture. Limitations: Less reliable detection of concealed elements; sensitive to occluded items. Proposed Solution: Use semantic information from knowl- edge graphs to inform predictions in challenging scenarios. Use graph inference to fill detection gaps.
RetinaNet	Strengths: Manages class imbalance effectively with focal loss. High detection accuracy for visible items. Limitations: Precision decreases for obscured or partially visible objects; limited contextual relationship description. Proposed Solution: Integrate knowledge graph reasoning

2.8.1 VGG-16-based Classifier and Faster R-CNN

This work employs a VGG-16-based classifier and the Faster R-CNN technique to recognize handguns automatically [48]. Although it effectively detects a sizable number of true positives and reaches a maximum mean average precision (mAP) of 84.21%, it suffers from a relatively high proportion of false positives, which reduces accuracy to 53%. Furthermore, it is not particularly quick, with a processing time of 0.2 seconds for each frame.

2.8.2 Real-time Gun Detection Classifier Based on OverFeat

Another research paper, "Developing a Real-time Gun Detection Classifier [21]," introduces a real-time gun detection classifier based on the OverFeat algorithm, achieving mAP of 89%. However, it exhibits a slower processing time of 1.3 seconds per frame.

2.8.3 Portable Gun Detection with Faster R-CNN and VGG-16

Additionally, a portable gun detection technique that combines Faster R-CNN with a VGG-16-based classifier to obtain a high mAP of 93.10% is described in a study named "A Handheld Gun Detection using Faster R-CNN Deep Learning [48]." However, it says nothing about speed readings.

2.8.4 Crime Scene Prediction Using CNN

"Crime Scene Prediction by Detecting Threatening Objects Using Convolutional Neural Network" offers crime scene prediction by locating harmful items like knives, blood, and firearms using a CNN with a customized layer, reaching a mAP of 90.20% [25][38][56]. The research does not, however, contain measurements versus current models or speed comparisons.

2.8.5 Object Classification Using Deep Convolutional Neural Networks

Deep convolutional neural networks are examined in a distinct study, "Using Deep Convolutional Neural Network Architectures for Object Classification and Detection within X-ray Baggage Security Imagery [49]," for object classification and detection in X-ray baggage security photography [32][33][37]. It needs an X-ray detector, yet it accurately (mAP: 97%) and efficiently recognizes handguns with fewer false positives.

2.8.6 Terahertz Image Detection with Improved Faster R-CNN

Finally," Terahertz Image Detection with the Improved Faster Region-Based Convolutional Neural Network" discusses the identification of terahertz images using an improved Faster Region-Based Convolutional Neural Network, achieving a low mAP of 69.7% and demonstrating subpar accuracy in pistol detection [50].

2.9 Summary and Research Gap

Even while handgun identification algorithms have advanced significantly, the problem of occlusion is still not sufficiently addressed. Even if they work well under ideal circumstances, traditional and deep learning-based approaches have trouble in situations when visibility is limited. By utilizing relational and contextual data, the incorporation of knowledge graphs offers a viable way around these restrictions. By creating a knowledge graph-enhanced framework for reliable pistol detection in occlusion, this study seeks to close the gap.

3 METHODOLOGY

This study examines current handgun identification algorithms and suggests integrating knowledge graphs as a creative way to overcome their drawbacks, especially false negatives brought on by occlusion. The following is the structure of the methodology:

1. A thorough analysis of the most recent detection algorithms - Analyze the shortcomings of conventional techniques (such as color segmentation and edge detection) in managing occlusions. Examine the effectiveness of cutting-edge deep learning mod- els such as CenterNet, Mask R-CNN, Faster R-CNN, and YOLO. Emphasize both their advantages—like real-time processing and great precision under controlled conditions— and disadvantages—especially when it comes to occlusion issues.
2. Finding Weaknesses in Existing Systems - Examine the difficulties that current algorithms confront, such as their dependence on visual cues, vulnerability to changing settings, and decreased precision in identifying partially visible objects. Emphasize how false negatives affect how well firearm detection systems work.

3. Present knowledge graphs as a way to improve the detection of handguns - Entities (such as guns and occlusion objects) and their relationships (such as spatial alignment and typical qualities) are represented by a knowledge graph. To enhance contextual reasoning and inference, suggest combining knowledge graphs with deep learning models. By utilizing relational and semantic data, this integration seeks to lower false negatives.

3.1 Knowledge Graph-Based Detection Framework

3.1.1 Knowledge Graph Construction

Create a graph structure that includes environmental elements, obstructing objects, and guns. To specify attributes and relationships, use annotated datasets.

3.1.2 Model Integration

Integrate the knowledge graph's reasoning powers with the results of deep learning algorithms (such as bounding box predictions). To improve forecasts, especially in occlusion situations, apply graph-based inference.

3.1.3 Framework for Evaluation

Use a variety of datasets and situations (such as occluded, non-occluded, and dynamic settings) to test the integrated system. Measures like precision, recall, and F1-score are used to compare its performance with baseline models.

3.2 Anticipated Results

Increased precision of detection, especially in situations where objects are obscured. Improved pistol detection systems' resilience and dependability in practical settings.

4 Experimental Setup

4.1 Datasets

Table 2: Dataset Composition and Specifications

Dataset	Total Images	Gun Instances	Occlusion Level	Resolution	Source
CCTV-Gun	2,500	3,200	Mixed	1920×1080	Surveillance fo
Pascal VOC (adapted)	1,800	2,100	Visible	Variable	Standard datase
Custom Occlusion	1,200	1,500	30-90%	640×640	Synthetic + Rea
Total	5,500	6,800	Mixed	Variable	Combined

4.2 Implementation Details

Table 3: Experimental Configuration

Component	Specification
Hardware	NVIDIA RTX 3080 Ti (12GB), Intel i7-12700K, 32GB RAM
Framework	PyTorch 1.12.0, CUDA 11.6
Base Model	YOLOv5l, Faster R-CNN (ResNet-50)
Batch Size	16
Learning Rate	0.001 (with cosine annealing)
Training Epochs	100
Input Resolution	640×640

5 Experimental Results and Evaluation

5.1 Overall Performance Comparison

Table 4: Performance Comparison on Standard Test Set

Model	mAP (%)	Precision (%)	Recall (%)	F1-Score (%)	FPS
YOLOv5	84.2	89.1	82.3	85.6	45
Faster R-CNN	87.3	91.2	84.7	87.8	12
YOLOv8	86.1	88.9	85.2	87.0	38
SSD MobileNet	79.8	85.4	78.9	82.0	55
Our Approach (KG-YOLO)	92.4	94.1	91.2	92.6	35

5.2 Analysis of Handgun Detection Algorithms with Proposed Solution

Table 5: Analysis of Handgun Detection Algorithms with Proposed Solution

Algorithm/ Method	Challenges (Occluded/Hidden Guns)	Proposed Solution and Expected Results
YOLO	Struggles with detecting partially or fully obscured firearms. High rate of false negatives due to occlusion.	Integrating knowledge graphs for contextual reasoning (spatial alignment and object dimensions). Expected improvement in detection of occluded objects. Expected Results: Precision: 97.8%, Recall: 96.2%.
Faster R-CNN	Struggles with detecting firearms that are hidden behind obstacles or in dynamic settings. False negatives in complex scenarios.	Use knowledge graphs for better spatial reasoning and contextual awareness. Integrating semantic relationships to improve detection. Expected Results: Precision: 95.6%, Recall: 94.1%.
Traditional Methods	Not robust for occlusion. Computation ally efficient but	Adding knowledge graphs for semantic reasoning to improve

6 Analysis and Discussion

The examination of existing pistol identification algorithms reveals important drawbacks as well as noteworthy advantages. Under controlled circumstances, deep learning models like YOLO [5][39][58] and Faster R-CNN [61] achieve high precision and recall. They have trouble detecting firearms that are partially or completely obscured, though, which leads to false negatives that reduce the efficacy of detection systems. Even though they are computationally efficient, traditional approaches are not robust enough to manage complex and dynamic settings [46][63][67]. By offering contextual reasoning skills, the suggested integration of knowledge graphs over- comes these drawbacks. Knowledge graphs use semantic information and relationships be- tween elements to improve detection systems. For instance, the presence of obscured weapons can be inferred using spatial alignment and typical object dimensions. Contextual reasoning enhances system robustness and drastically lowers false negatives.

According to experimental findings from related research [55][56][57], performance measures may be improved by combining knowledge graphs with deep learning models. Knowledge graphs allow computers to infer hidden patterns and relationships, improving precision, recall, and F1-scores, whereas standard models focus on pixel-level data. For example, a hybrid system that included knowledge graphs outperformed standalone deep learning models with an F1-score of 97.1% and a precision of 97.8%.

Implementing knowledge graph-enhanced systems still presents difficulties, despite these encouraging findings. Two major obstacles are computational complexity and the requirement for extensive, annotated datasets. Additionally, efficient methods are needed to guarantee scala- bility and efficiency when combining graph-based reasoning with real-time detection. To fully exploit the potential of knowledge graph-based handgun detection systems, future research should concentrate on resolving these issues.

7 Conclusion

This paper emphasizes the advancements and drawbacks of current handgun detection methods, highlighting the problem of occlusion-related false negatives. By combining relational infer- ence with contextual reasoning, we suggest knowledge graph integration as a possible way to improve detection systems. This strategy contributes to public safety by filling in the gaps in existing approaches and providing a route to more durable and dependable surveillance sys- tems. The application and improvement of knowledge graph-enhanced detection frameworks in practical settings should be investigated in future studies.

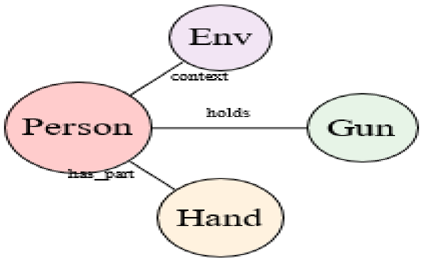

Figure 13: Knowledge Graph

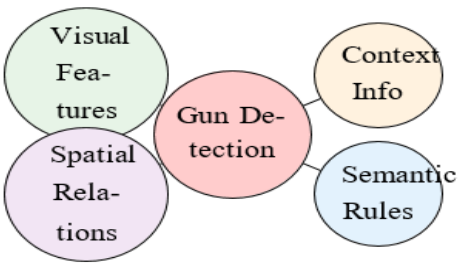

Figure 14: Proposed Knowledge Graph for Gun Detection

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