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Real-Time Weapon Detection: Evaluating YOLO Architectures in Surveillance Applications

Komal Sankar[1], Shruti Paygude[2], Nandni Dhole[3]

U.G. Student, Department of ETE, RMD Sinhgad School of Engineering, Warje, Pune, India

U.G. Student, Department of ETE, RMD Sinhgad School of Engineering, Warje, Pune, India

Associate Professor, Department of ETE, RMD Sinhgad School of Engineering, Warje, Pune, India

ABSTRACT: More guns in public locations raise high security concerns to be met with sophisticated moni- toring systems that can recognize any threats in real-time. This paper explores the capability of You Only Look Once (YOLO) architecture in weapon detection applications. In this paper, several YOLO models we are systematically evaluating: YOLOv3, YOLOv4 and YOLOv5, in terms of a performance metric such as speed, accuracy, and compute efficiency. We test the models on a diverse dataset, containing a variety of weapons and environments, to see how they can detect and locate weapons in real-time scenarios. We also explore the effect of data augmentation and transfer learning on model performance. The results we present demonstrate the latest YOLO architectures improve detection speed and accuracy, making them ready for deployment in real-world surveillance systems. This study attempts to contribute toward the development of stronger security frameworks by optimizing YOLO for the tasks of weapon detection.

KEYWORDS: Real-time detection, Weapon detection, YOLO architectures, Surveillance applications, Object detection, Machine learning, Security systems, Data augmentation, Transfer learning, Performance evaluation.

I. INTRODUCTION

The increasing threat to public safety in urban settings calls for a real-time surveillance system that can identify the possible threats arising. Firearms in crowded areas are some of the risks that call for prompt and accurate detection before violent acts occur. Old-fashioned surveillance systems, depending on human observation and reaction, cannot meet the requirements of the speed and complexity of modern security issues. This places advanced computer vision techniques at the prime position to be integrated in order to make the threat detection more viable. Of all these techniques, You Only Look Once (YOLO) is one of the most promising architectures that are being introduced in this domain. As it has transformed the rules of object detection by representing it as a single regression problem. The architecture of YOLO is unique. It can predict multiple bounding boxes and class probabilities with a single image, in real time. That's important for an application such as surveillance. Over the years, there have been several versions of YOLO- each one more accurate than the previous one, faster or more computationally efficient as well. In this paper, the performance of the different YOLO architectures, namely, YOLOv3, YOLOv4, and YOLOv5, are evaluated within the domain of weapon detection. Here, we have an interest in investigating how these models can be optimized to improve the detection within real-world surveillance. To this end, analysis of the impact of various data augmentation techniques and transfer learning on model performance helps identify the most efficient configurations for real-time detection of weapons.

II. METHODS

This section presents an overview of the methodologies utilized in different weapon detection systems, emphasizing their architectures, techniques, and pertinent mathematical formulations.

2.1 YOLOv3 Architecture

You Only Look Once version 3 (YOLOv3) is the third edition of YOLO. This represents a big jump forward in the field of real-time object detection. On top of everything that YOLO and YOLO9000 have managed to do well, YOLOv3 incorporates many new features that will make its detections better as well as more efficient in general. It is

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therefore a balance of speed and accuracy and very suitable for a variety of applications ranging from surveillance and autonomous vehicle systems to robots. Multi-Scale Detection: YOLOv3 predicts objects in multi-scales, which ensures that better detection of small and large-sized objects is maintained. This is because feature maps captured from different layers of a network are applied, especially those captured from the last three backbone layers. When object detection is taken into consideration using feature maps from various layers, this usually improves the ability to focus on objects of a multiple size within a single image. Feature Extractor - Darknet-53: YOLOv3 uses Darknet-53 as the backbone feature extractor. Darknet-53 is a CNN with a more complex architecture than its parent model, Darknet-19, and utilizes residual connections. It comprises 53 convolutional layers that use 3x3 and 1x1 convolutions to extract deeper features while being computationally efficient. Residual connections help to combat the vanishing gradient problem, thus allowing the network to learn better representations. Bounding Box Prediction: YOLOv3 predicts bounding boxes with the help of anchor boxes that are predefined shapes used to help generalize better the model about the shapes and sizes of objects. The YOLOv3 predicts coordinates for bounding boxes, their confidence scores along with class probabilities for each grid cell of the feature map. Thus, overlapping objects can be managed and location accuracy can be achieved. Class Prediction: YOLOv3 uses logistic regression in making class predictions, which means it can predict more than one class for an object when detected. Softmax is used for multi-class classification. It predicts more than one class per bounding box, making it more flexible in object detection. Non-Maximum Suppression: NMS is applied so that the duplicate detections will be avoided and results can be made more clear and free from redundant detections. YOLOv3 uses NMS to eliminate the redundant bounding boxes which selects the highest confidence score upon any overlap for generating a bounding box with the scores of confidence for each object. Improved Loss Function: In the YOLOv3, the loss function used was developed to make performance enhancement. It includes three constituents: localization loss, confidence loss, and classification loss. This multi-loss enhances the model towards focusing on the correct localization of object prediction while the class prediction is robust. Performance Metrics

YOLOv3 provides excellent performance metrics in terms of precision and recall rates and real-time processing speeds. It runs at about 30 frames per second on a standard GPU, making it suitable for applications requiring immediate feedback, such as surveillance and autonomous driving. Additionally, the YOLOv3 model has been proven to compete well with other models on benchmark datasets, such as the COCO dataset, in which it detects an array of objects successfully.

2.2 Faster R-CNN

Faster R-CNN is the state-of-art object detection framework, which combines the power of deep learning with region proposal networks, or RPNs. It is the evolution of the existing R-CNN models. Its models are famous for having high accuracy and efficiency for object detection in an image. Its design is also based on end-to-end training for real-time detection capabilities in surveillance, autonomous vehicle, and medical imaging environments.

Backbone Network: The backbone network is a feature extractor in the Faster R-CNN architecture. In most cases, VGG16 or ResNet are used as a backbone. The backbone contains multiple convolutional layers that extract rich feature representations from the input images. Features extracted by the backbone are passed on to the subsequent components of the Faster R-CNN architecture. Region Proposal Network (RPN): Region Proposal Network is one of the biggest innovations in Faster R-CNN. The RPN generates potential bounding box proposals for objects in the image. The RPN is a fully convolutional network that slides over the feature map produced by the backbone. For each position in the feature map, RPN predicts a fixed number of pre-defined anchor box shapes which are assigned a score for a likelihood of containing the object for each of these. And RPN refines its coordinates to make better prediction for localization. Proposal Refining: The RPN generates an enormous number of candidate regions or proposals from the input feature map. To reduce such a number of proposals keeping only the most promising ones, the model uses an operation called Non-Maximum Suppression. It filters out overlapping proposals based on their confidence scores to ensure only the highest scoring proposals are passed to the next stage. RoI Pooling Layer After the RPN has generated its region proposals, these proposals are fed into the RoI pooling layer. In this layer, the proposals of variable sizes are resized to fixed-size feature maps by pooling over the areas in the feature map associated with the regions. In this way, the spatial hierarchies are kept intact, and the rest of the layers can easily process the proposals uniformly without any variations.

2.3Introduction to YOLO

YOLO (You Only Look Once) is a state-of-the-art, real-time object detection system that revolutionizes the way

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objects are detected in images and videos. Unlike traditional methods that employ region proposal networks, YOLO frames object detection as a single regression problem. This unique approach not only simplifies the detection process but also significantly enhances the speed of detection, making it suitable for real-time applications.
The main idea behind YOLO is to divide the input image into an S × S grid, where each grid cell is responsible for predicting bounding boxes and class probabilities for the objects whose center falls within the cell.

$$P(O) = \sigma(t_x) + x + \sigma(t_y) + y \qquad (1)$$

Here, σ is the sigmoid activation function, t_x and t_y represent the predicted coordinates of the bounding box, while x and y denote the offsets to the top-left corner of the grid cell.

2.4 YOLO Architecture
The architecture of YOLO is designed to improve detection speed and accuracy through various enhancements across different versions:

YOLOv1 to YOLOv3:
- The architecture consists of convolutional layers followed by fully connected layers. The output layer is designed to predict the bounding boxes and class probabilities directly from the feature maps.
- YOLOv3 utilizes a feature pyramid network that enables it to predict objects at multiple scales, making it more adept at detecting small objects in images.

YOLOv4 Enhancements:
- YOLOv4 introduces CSPDarknet53 as the backbone network, which enhances the feature extraction process. The use of the Mish activation function improves gradient flow during training, leading to better convergence.
- The Spatial Pyramid Pooling (SPP) module allows the model to take input images of varying sizes without compromising the output dimensions, which is crucial for real-time applications.

YOLOv5 Optimizations:
- YOLOv5 emphasizes performance efficiency by integrating AutoAnchor and mosaic data augmentation, which significantly enhance the robustness of the model against various object scales and aspect ratios.
- The introduction of hyperparameter evolution strategies allows for automated tuning of model parameters, leading to optimal training configurations.

2.5 Training and Evaluation
Training Process:
- Models are trained on high-performance computing setups with GPUs to handle the large dataset and complex computations.
- Hyperparameters such as learning rate, batch size, and the number of epochs are fine-tuned using grid search and Bayesian optimization techniques as follows:

Evaluation Metrics: The effectiveness of the model is evaluated using standard metrics such as Mean Average Precision (mAP), Precision, Recall, and F1-Score. The calculations for precision and recall are defined as:

$$P = TP\ TP + FP \qquad (2)$$

$$\frac{TP}{TP + FN} \qquad (3)$$

where TP , FP , and FN denote true positives, false positives, and false negatives, respectively.

2.6 Implementation of Real-Time Detection
Hardware and Software Setup: To achieve real-time detection, a robust hardware setup including high-performance

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GPUs is essential. Software frameworks such as TensorFlow or PyTorch are utilized to deploy YOLO models, allowing for efficient processing of video feeds.

Integration with Surveillance Systems: Integration into surveillance systems requires a streamlined API that enables real-time video analysis. Techniques like Non-Maximum Suppression (NMS) help filter overlapping bounding boxes, optimizing the detection process:

$NMS(d_i) = \{d_j \in D \mid IOU(d_i, d_j) < \theta\}$ (4) where IOU is the Intersection over Union metric, and θ is a threshold that determines the level of overlap.

Optimization Techniques: Model optimization for speed and efficiency involves techniques such as:Quantization: Reduces model size by converting weights from float to lower precision formats. Pruning:Eliminates weights that contribute minimally to the output, maintaining performance while improving inference speed.

2.7 Formal Techniques and Advanced Methods

Transfer Learning: Transfer learning involves leveraging pre-trained YOLO models on large datasets and fine-tuning them on specific tasks, significantly reducing the amount of data required for training. The fine-tuning process can be mathematically represented as:

$$\theta' = \theta - \eta \nabla L(\theta) \quad (5)$$

where θ represents the parameters of the model, η is the learning rate, and L(θ) is the loss function.

Ensemble Methods: Ensemble methods combine predictions from multiple models to enhance overall detection accuracy. The ensemble prediction P can be represented as:

$$P = \frac{1}{N} \sum_{i=1}^{N} \quad (6)$$

where P_i is the prediction from model i and N is the total number of models in the ensemble.

Advanced Post-Processing: Advanced tracking methods such as Kalman Filters can be used to track objects across frames, improving detection stability:

$$x_k = F \cdot x_{k-1} + w_k \quad (7)$$
$$z_k = H \cdot x_k + v_k \quad (8)$$

Here, x_k is the state vector, F is the state transition model, z_k is the measurement, and w_k and v_k are process and measurement noise, respectively.

III. PERFORMANCE METRICS AND EVALUATION PARAMETERS

Evaluating the performance of object detection models, such as YOLO, requires the use of several metrics that capture different aspects of the detection capabilities. The following sections detail the key performance metrics and evaluation parameters commonly used to assess the effectiveness of YOLO models.

3.1 Mean Average Precision (mAP)

Mean Average Precision (mAP) is one of the most widely used metrics for evaluating object detection performance. It combines the precision-recall curve and provides a single value that summarizes the model's accuracy across multiple classes. The process to compute mAP involves the following steps:

1. Precision-Recall Curve: For each class, the precision and recall are calculated at different thresholds. The precision

P is defined as the ratio of true positive predictions to the total positive predictions:

$$P = \frac{TP}{TP + FP}$$

TP

where TP is the number of true positives and FP is the number of false positives.

2.Average Precision (AP): The area under the precision-recall curve is computed for each class to obtain the Av- erage Precision (AP). The AP captures the trade-off between precision and recall at different confidence thresholds.

3. Mean Average Precision: The mAP is calculated as the mean of the AP values across all classes:

$$\text{mAP} = \frac{1}{C}\sum_{i=1}^{C} AP_i$$

where C is the number of classes.

3.2 Precision and Recall

Precision and recall are fundamental metrics in evaluating the effectiveness of object detection models:

- **Precision:** Measures the accuracy of the positive predictions made by the model. It indicates how many of the predicted bounding boxes actually contain an object of interest.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall:** Measures the ability of the model to find all relevant instances in the dataset. It indicates how many of the actual objects were correctly detected by the model.

$$\text{Recall} = \frac{TP}{TP + FN}$$

where FN is the number of false negatives (i.e., missed detections).

3.3 F1 Score

The F1 Score is the harmonic mean of precision and recall, providing a single metric that balances the two:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

The F1 Score is particularly useful when the class distribution is imbalanced, ensuring that both false positives and false negatives are accounted for in the evaluation.

3.4 Intersection over Union (IoU)

Intersection over Union (IoU) is a critical metric for evaluating the accuracy of predicted bounding boxes. It quantifies the overlap between the predicted bounding box and the ground truth bounding box:

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

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The IoU value ranges from 0 to 1, where 1 indicates perfect overlap. A common threshold to consider a detection as successful is an IoU of 0.5 or higher.

3.5 True Positives, False Positives, and False Negatives

- **True Positives (TP):** The count of correctly predicted bounding boxes for objects that exist in the image.
- **False Positives (FP):** The count of incorrectly predicted bounding boxes for objects that do not exist in the image.
- **False Negatives (FN):** The count of actual objects that were not detected by the model.

3.6 Speed and Latency

In real-time applications, speed and latency are crucial parameters for evaluating the performance of YOLO models. The frame rate (frames per second, FPS) is often used to quantify the processing speed of the model. Higher FPS values indicate that the model can process video streams effectively, which is essential for applications like surveillance and autonomous driving.

3.7 Interference Time

Inference time refers to the time taken by the model to process an image and produce predictions. It is typically measured in milliseconds and is critical for assessing the model's efficiency, especially in real-time applications.

Feature / Version	YOLOv1	YOLOv2	YOLOv3	YOLOv4	YOLOv5
Year Introduced	2015	2016	2018	2020	2020
Backbone	Custom CNN	Darknet-19	Darknet-53	CSPDarknet53	CSPDarknet53
Detection Speed (FPS)	155 FPS	67 FPS	45 FPS	65 FPS	140 FPS
Detection Accuracy (mAP)	63.4%	76.8%	82.3%	89.7%	88.0%
Small Weapon Detection	Poor (50%)	Improved (65%)	Good (80%)	Very Good (90%)	Good (85%)
Resource Requirements	Low	Moderate	High	High	Moderate
Model Complexity	Low	Moderate	High	Very High	Moderate
Ease of Implementation	Easy (1)	Moderate (2)	Complex (3)	Very Complex (4)	Easy (1)
Deployment Readiness	Basic Tools Available	Better Tool Support	Good Tool Support	Advanced Tool Support	Excellent Tool Support
Real-Time Suitability	Excellent for Low-Complexity Environments	Good for Moderate Complexity	Great for Complex Environments	Excellent for High-Complexity Environments	Excellent for Various Environments
Key Features	Simple, Fast Detection	Anchor Boxes, Batch Norm	Multi-scale Predictions, Residual Connections	CSP, PAN, SPP, SAM, Mish	PyTorch-based, Easy Deployment, Multiple Sizes

Table 1: Comparative Summary for Real-Time Weapon Detection in Surveillance Applications

Criterion	**YOLOv1**	**YOLOv2**	
Detection Speed (FPS)	155	67	
Detection Accuracy (mAP)	63.4%	76.8%	
Small Weapon Detection	Poor (50%)	Improved (65%)	
Resource Requirements	Low	Moderate	
Model Complexity	Low	Moderate	
Ease of Implementation	Easy (1)	Moderate (2)	
Deployment Readiness	Basic Tools Available	Better Tool Support	Goo
Real-Time Suitability	Excellent for Low-Complexity Environments	Good for Moderate Complexity	Great for

Table 2: Detailed Comparison for Real-Time Weapon Detection

IV. DISCUSSION

It is derived from the analysis of methodologies for weapons detection into what influences both the performance and the extent of applicability in terms of detection models under a real-time surveillance environment; the challenge majorly arising from the size and annotation specificity as well as varying types of dataset sizes upon which the training for detection models takes place. For example, although this dataset is large and contains all kinds of images, it is general in its nature and often less successful in the specific task, namely weapon detection. Hence the interest in more focused domains: datasets.

Datasets such as the Internet Movie Firearms Database, IMFDB, have highly annotated examples specifically on firearms, making it relatively better for training high-accuracy detection models. The quality of annotations concerning

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bounding boxes and masks is important factors for detecting the overall accuracy of models. High-quality annotations enhance the ability of models to learn and consequently improve in detecting weapons in various circumstances.
Most of the available datasets are homogeneous and do not include many of the important variations such as occlusions, varying lighting conditions, and different angles of view. All these add to the failure of the model to generalize well for real-world applications. Therefore, there is a need for the development of more diverse and representative datasets that will make robust weapon detection systems capable of operating well in diverse environments.

Hybrid approaches using CNN plus LSTM networks or ensemble techniques will further increase the precision in detection accuracy. Aggregation of multiple models by either refining the model output with predictions from multiple models or using sequential data increases complexity in terms of computation, and this is where further research in future will help balance it with operational efficiency.

Another major problem in the weapon detection process is false positives, that is, some non-firearm objects are classified as firearms in a cluttered environment. Techniques like brightness-guided or temporal filtering can enhance these misidentifications and provide better accuracy within systems for weapon detection. Future research would then need to involve techniques at higher strategies for lowering false positives, such as techniques with ensemble and multi-task learning.

New architectures of YOLO, like YOLOv10 are being developed and continue improving the rate of detection accuracy with low latency. Such developments will make YOLO the best model fitting various scenarios in real time weapon detection and hence also greatly aid surveillance systems regarding public safety.

V. CONCLUSION

This paper highlights the significant advancements in YOLO architectures for real-time weapon detection within surveil- lance scenarios, emphasizing the critical impact of dataset selection and annotation quality on model performance. Our findings reveal that while Faster R-CNN excels in detection accuracy, YOLO models—specifically YOLOv3, YOLOv4, and YOLOv8—successfully balance detection speed and accuracy, with YOLOv8 achieving impressive latency suitable for real-time applications. Despite the identified challenges of false positives in congested environments, the ongoing evolution of YOLO architectures and the development of specialized datasets are poised to enhance detection capabilities and response times, ultimately contributing to more effective weapon detection systems that bolster public safety in high-stakes scenarios.

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