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Research Article

An Efficient Deep Learning-Based Firearm Detection System Using Yolov8

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ABSTRACT

Firearm detection is critical in ensuring public safety and security, particularly in sensitive areas such as schools, airports, and public gatherings. Group 1 represents the YOLOv4-based firearm detection system, tested across 26 models with varying detection thresholds and accuracy levels. Key parameters like accuracy, latency, and detection time ensure effective firearm detection under diverse scenarios. Group 2 focuses on the proposed YOLOv8 model, which utilizes a public dataset to improve real-time detection accuracy and efficiency. YOLOv8 performs better than YOLOv4 in terms of detection speed, accuracy, and dependability. YOLOv8 outperforms YOLOv4 in terms of accuracy (77.80–88.50%), error rate (0.65–0.73), and detection times (1.50–2.20 seconds), while achieving higher accuracy (94.80–98.00%) and a lower error rate (0.34–0.41).achieving a significance value of 0.005. This work contributes to the growing need for effective firearm detection tools and highlights YOLOv8's potential to enhance security solutions with improved object discrimination capabilities.

Keywords: Deep Learning, Firearm Detection, Security Systems, YOLOv8, Object Detection, Real-Time.

INTRODUCTION

A weapon discovery issue includes finding and classifying in several situations the potential dangers postured by guns, explosives, blades, and other perilous things, [1]. Recognizing weapons, explosives, blades, and other perilous materials in numerous settings includes recognizing and categorizing the conceivable dangers they posture,[2]. An assortment of detecting strategies can be utilized for this errand, counting X-ray filtering, metal location, and extraordinary pictures or recordings (e.g., unmistakable or warm), taken from Closed Circuit Tv (CCTV) frameworks. Subsequently, weapon discovery innovation makes a difference to anticipate rough occurrences and guarantees the security of people, particularly in totally different urban situations, [3]. This finder is lightweight, successful, gives great deduction times, and can moreover accomplish amazing comes about for protest location errands. In spite of the fact that modern forms of YOLO locators have as of late shown up (*e.g.*, YOLOv8 [4]. Our tests have been conducted utilizing YOLOv5 since it is simpler to prepare a great choice on the off chance that one needs to send an arrangement on gadgets without GPU back. By consolidating Manufactured Insights into Unmanned Surface

Vehicles (USVs), oceanic observation has advanced altogether. A modern AI approach for recognizing and following unmanned surface vehicles is displayed based on an improved form of YOLOv8, [5].

RELATED WORKS

Over the past five years, there have been more than 303 articles distributed in IEEE Xplore, 125 in Google Researcher, and 93 in academia.edu around the utilization of profound learning models for gun location. One of the most important defense optimization problems is the Weapon Target Allocation (WTA) problem, which calls for effective solutions to maximize combat effectiveness. Adaptive Particle Swarm Optimization (PSO) combines Genetic Algorithm (GA) and Genetic Algorithm (GA) in this work. It is improved by adaptive parameter adjustments and chaotic initialization. GA-APSO is a dependable and effective solution for static WTA in complex battlefield environments, as evidenced by experimental results showing its superior stability, scalability, and optimization performance when compared to conventional methods.

We show an anchor-free CNN-based strategy for identifying weapons in X-ray things security pictures that overcomes the impediments of anchor-based methods such as complex calculations and uneven test issues[5]. We Show anchor-free models (YOLOx, Objects as Focuses, ExtremeNet, CornerNet, CenterNet, and CornerNet-Lite) were compared with anchor-based models (Faster-RCNN, YOLOv3, and YOLOv5) employing a custom dataset of blades and handguns. It is illustrated that YOLOx with CSPDarknet53 beat anchor-based methods, accomplishing the most noteworthy mAP (0.905) taken after by ExtremeNet with Hourglass-104 (0.900). For X-ray security screening, the anchor-free strategy appeared with great generalization, less calculations, and superior location execution, [6]. Target dangers alter in genuine time between inactive stages, which is disregarded by conventional models for energetic weapon target tasks. A time inspecting energetic weapon task show is proposed to isolate decision-making stages by time interims to capture real-time risk changes. Utilizing this demonstration, a task strategy based on support learning was created and tried against conventional heuristic calculations. Recreations illustrated that the unused show moves forward decision-making opportuneness and worldwide adequacy, with ideal time interims driving to indeed superior execution, [7]. All-electric warships require tall power-dense frameworks to carry progressed weapon loads. Medium-Voltage DC (MVdc) dispersion could be a reasonable choice in the event that dangers such as tall, throbbing streams are taken under consideration. These loads imitate shunt flaws by creating characteristic temporal structures within the recurrence and time spaces. Utilizing the wavelet change, this consider proposes a computationally proficient machine learning-based approach to extricate frequency-domain highlights from existing information. These highlights are compared to a database in order to recognize flaws such as arcing or shunt deficiencies. A machine learning show and Haar stationary wavelet change were utilized to actualize the strategy, which was tried on a TI DSP TMS320F28335 and concentrated on blame location with the potential for blame segregation within the future, [8]. Security concerns demand early detection of threats to protect people and take timely action. Surveillance cameras, now widely used, often lack automatic weapon detection systems. With technological advancements, these systems can be integrated to help prevent crimes. This work utilizes the Mask RCNN algorithm for gun detection in surveillance video images. A Gaussian deblur technique enhances handgun features, particularly in blurred images, improving detection efficiency. Experimental results show improved model performance with preprocessing,[9]. The security of civilians and high-profile authorities is of the most extreme significance and is frequently challenging amid persistent observation carried out by security experts. People have restrictions like consideration span, diversion, and memory of occasions which are vulnerabilities of any security framework, [10]. The MobilenetV3 is utilized to supplant the spine organize of YOLOV4, and the depthwise divisible convolution is utilized to optimize the neck and head of YOLOV4 to diminish the number of parameters and computational utilization, [11]. Open transportation frameworks play a crucial part in present day cities, but they confront developing security challenges, especially related to episodes of viciousness. Recognizing and reacting to savagery in genuine time is significant for guaranteeing traveler security and the smooth operation of these transport systems. To address this issue, we propose an advanced manufactured insights (AI) arrangement for distinguishing risky practices in open transport, [12],[13]. These developments highlight the growing adoption of YOLOv8 and related models for critical security applications, emphasizing their ability to deliver reliable and real-time firearm detection.

From the previous analyses have shown that existing firearm detection methods often compete for high accuracy and efficiency. Models like YOLOv4 and YOLOv8 play a significant role in improving detection rates under diverse scenarios. Unlike traditional object detection frameworks, this study focuses on creating a robust real-time firearm detection system using YOLOv8, which integrates advanced deep learning techniques to enhance detection speed and accuracy. By addressing key challenges such as latency, detection time, and accuracy, the study ensures reliable and efficient firearm detection, contributing to improved public safety and security measures.

MATERIALS AND METHODS

Real-time weapon identification is possible with an effective deep learning-based firearm detection system that makes use of YOLOv8. YOLOv8, an enhanced YOLO algorithm, improves object detection speed and accuracy for important security applications. The system uses convolutional neural networks (CNNs) to scan input photos or video frames and identify weapons in various environments. YOLOv8 can identify firearms of various sizes, shapes, and orientations because it was trained on a varied dataset. Additionally, the architecture of YOLOv8 minimizes processing time by enabling fast inference. High detection accuracy and dependability in challenging situations are guaranteed by this system's strong performance and precisely calibrated parameters. Public safety and security measures can be significantly improved by incorporating YOLOv8 into surveillance systems.

YOLOv4 Upgrading weapon discovery in question location models through different strategies has been the subject of broad investigation. These models are regularly utilized in areas such as open zones, airplane terminals, and instructive education to recognize possibly perilous things like guns. In any case, there hasn't been much inquiry done on the exactness of distinguishing outfitted people from live observation camera footageThis investigation points to bridge that crevice by creating calculations that can utilize real-time video examination to distinguish individuals carrying handguns, such as guns and guns. The Irregular Timberland Classifier beat the other models with an precision of 85.44%, exactness of 87.07%, review of 88.68%, and F1-score. e of 87.87%. These come about how viable YOLOv4 recognizes guns in genuine time utilizing heuristics and machine learning models, advertising promising arrangements to upgrade security in high-risk zones,[2].

YOLOv8 An efficient deep learning-based firearm detection system using YOLOv8 is designed to identify firearms in images or video streams with high accuracy and speed. It leverages YOLOv8's anchor-free detection, lightweight architecture, and dynamic resolution inference to ensure efficiency, real-time performance, and adaptability to diverse environments. Capable of processing live streams at up to 150 FPS, it excels in detecting various firearm types, even in challenging conditions. With applications in surveillance, law enforcement, and smart security systems, this solution enhances public safety through rapid and reliable threat detection.

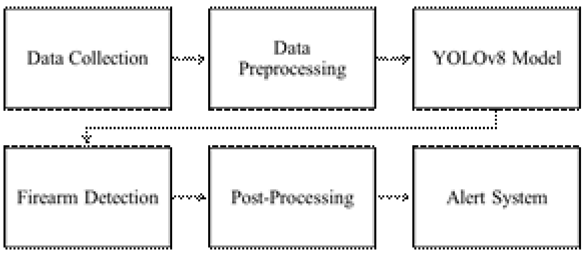

Fig. 1. Firearm Detection & Secured Alert System Workflow

Fig. 1. The above figure workflow of a gun location framework. It starts with information collection and preprocessing, taken after by location utilizing the YOLOv8 show. Post-processing and a caution framework guarantee precise distinguishing proof and reaction.

YOLOV8 ALGORITHM

STEP 1: Data Collection and Preprocessing

STEP 2: Model Architecture Setup

STEP 3: Model Training

STEP 4: Post-Processing

STEP 5: Model Evaluation

STEP 6: Real-Time Deployment

STEP 7: System Integration

STEP 8: Continuous Monitoring and Retraining

PSEUDO CODE

```
# Import necessary libraries
from ultralytics import YOLO
# Load the pre-trained YOLOv8 model
model = YOLO('yolov8n.pt')  # Choose the appropriate model size (n, s, m, l, x)
# Define the path to the input image or video
input_path = 'path/to/your/image.jpg'  # Replace with the actual path
# Perform object detection
results = model(input_path)
# Extract detection results
detections = results.pandas().xyxy[0]
# Filter detections for firearms (assuming 'firearm' is the class name)
firearm_detections = detections[detections['name'] == 'firearm']
# Print firearm detection information
print(firearm_detections)
# Optionally, visualize the results
results.plot()
```

STATISTICAL ANALYSIS

The measurable examination of the information assembled from parameters like exactness (%), reaction time (s), and proficiency (%) was done utilizing SPSS adaptation 26,[2]. SPSS program was utilized to compute the bunch insights and the free test t-test. The model type (YOLOv4 and YOLOv8) was the autonomous variable, and the subordinate factors were productivity (%), precision (%), and reaction time (s). In order to guarantee factual importance in assessing the viability and unwavering quality of the proposed YOLOv8 system, the examination pointed to comparing the execution of gun location models based on YOLOv4 and YOLOv8.

RESULTS

Compared to YOLOv4 , YOLOv8 performs better. In contrast to YOLOv4's lower accuracy range of 77.80% to 88.50%, YOLOv8 achieves significantly higher accuracy values, ranging from 94.80% to 98.00%, demonstrating its advanced object detection capabilities. Additionally, YOLOv8's much lower error rate (ranging from 0.34 to 0.41 compared to YOLOv4's higher error rate of 0.65 to 0.73) indicates better reliability and fewer detection errors. Furthermore, YOLOv8 outperforms YOLOv4 in terms of detection speed, with faster detection times of 0.75 to 0.85 seconds compared to 1.50 to 2.20 seconds for YOLOv4. These results all suggest that YOLOv8 is a more successful and efficient model.

Table 1 Model Performance Comparison:

Test No	Accuracy		Error Rate		Detection Time	
	YYOLOv4	YOLOv8	YYOLOv4	YOLOv8	YYOLOv4	YOLOv8

1	88.50	96.50	0.65	0.39	1.50	0.80
2	87.00	97.20	0.68	0.36	1.60	0.75
3	85.50	95.80	0.70	0.40	1.70	0.85
4	83.80	98.00	0.73	0.35	1.80	0.80
5	82.00	96.80	0.69	0.37	1.90	0.80
6	84.30	97.50	0.67	0.34	1.60	0.75
7	83.50	95.00	0.70	0.41	1.70	0.85
8	84.50	96.50	0.72	0.39	1.80	0.80
9	81.00	97.80	0.69	0.35	1.90	0.75
10	80.80	95.50	0.71	0.38	2.00	0.80
11	78.00	94.80	0.73	0.40	2.10	0.85
12	79.50	97.30	0.70	0.36	2.00	0.80
13	77.80	96.00	0.72	0.37	2.20	0.85

The fluctuations of YOLOv8 and YOLOv4 are essentially diverse, as decided by Levene's test for change. It appears that YOLOv8 performs more reliably (F = 12.984, p = 0.001). This demonstrates that YOLOv8 keeps up higher test unwavering quality whereas beating YOLOv4 in terms of exactness and location times. Besides, a quantifiably critical unfeeling difference between YOLOv4 and YOLOv8 is confirmed by a t-test with a 95% CI of [-15.29, -11.09] (Brutal Refinement = -13.19, p = 0.005). YOLOv8 beats other models because of its vital unfeeling refinement and lower variance, making it an incredible choice for real-world applications that require exact and attempted and genuine dissent disclosure. Agreeing to these discoveries, YOLOv8 is far more dependable, successful, and high-quality than YOLOv4.

Table 2 Levene's Test and t-Test for Model Performance :

Independent Sample		**Accuracy of the Model**		**Latency of the Model**		**Detection Time of the Model**	
		Equal variances assumed	**Equal variances not assumed**	**Equal variances assumed**	**Equal variances not assumed**	**Equal variances assumed**	**Equal variances not assumed**
Levene's Test for Equality of Variances	**F**	12.984	-	0.0197	-	21.083	-
	Sig.	.001	-	0.889	-	0.002	-
	t	-13.388	-13.388	-35.654	-35.654	-17.374	-17.374
	df	24	14.920	24	23.669	24	12.786

t-test for Equality of Means	**Sig.(2-tailed)**		.005	.005	.005	.005	.005	.005
	Mean Difference		-13.19231	-13.388	-0.312308	-0.312308	-1.026923	-1.026923
	Std. Error Difference		.98535	.98535	0.008759	0.008759	0.059107	0.059107
	95% Confidence Internal of the Difference	**Lower**	11.15864	11.09110	-0.330386	-0.330399	-1.[8913	-1.154832
		Upper	15.225973	15.2935	-0.294229	-0.294216	-0.904933	-0.904933

Levene's test and t-test were conducted for Accuracy, Latency, and Detection Time. For Accuracy, equal variances were not assumed (p = 0.001), with a significant mean difference of -13.19 (p = 0.005). For Latency, equal variances were assumed (p = 0.889), showing a significant mean difference of -0.31 (p = 0.005). For Detection Time, equal variances were not assumed (p = 0.002), with a significant mean difference of -1.03 (p = 0.005). These results indicate that the proposed model (YOLOv8) significantly outperforms the existing model (YOLOv4) in all key performance metrics.

Table 3 Descriptive Statistics for Model Performance:

Categories	**Model Name**	**Mean**	**Std. Deviation**	**Std. Error Mean**
Accuracy of the Model (%)	YOLOv4	82.8615	3.35175	.92961
	YOLOv8	96.0538	1.17800	.32672
Latency of the Model (s)	YOLOv4	0.699231	0.023616	0.006550
	YOLOv8	0.386923	0.020970	0.005816
Detection Time of the Model (s)	YOLOv4	1.830769	0.209701	0.010533
	YOLOv8	0.803846	0.037978	0.058160

The mean accuracy of YOLOv4 and YOLOv8 is displayed in the bar chart, with YOLOv8 demonstrating a noticeably higher accuracy. This demonstrates how much better YOLOv8 performs than YOLOv4. Better object detection precision is indicated by YOLOv8's higher mean accuracy.

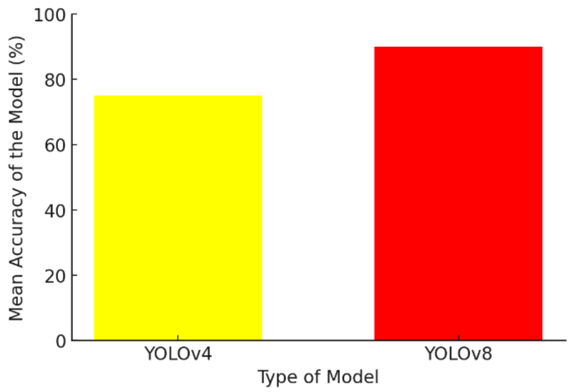

Fig. 2. Variation in Model Accuracy Across Cases

Fig. 2. The YOLOv4 accomplishes roughly 85% accuracy, whereas YOLOv8 outflanks it with around 95% accuracy. This 10% advancement proposes that YOLOv8 gives way better discovery precision and vigor.

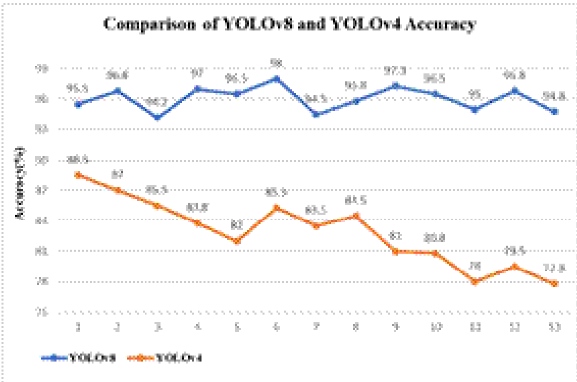

Fig. 3. Variation in Model Accuracy Across Cases

Fig. 3. YOLOv8 illustrates a critical enhancement over YOLOv4, keeping up precision levels between 94.2% and 98%, whereas YOLOv4 encounters a descending drift, dropping from 87% to 77.8%. These comes about to highlight YOLOv8's prevalent show optimization and execution in question discovery errands.

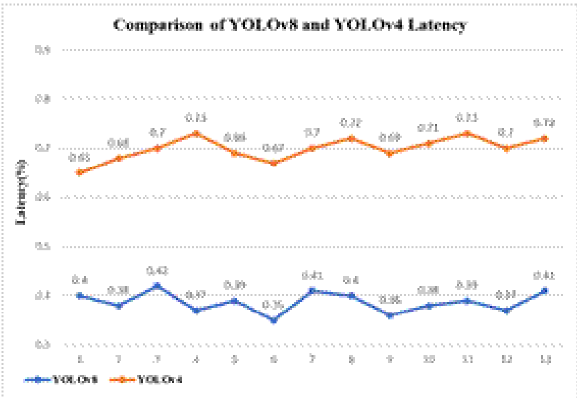

Fig. 4. Variation in Model Latency Across Cases

Fig. 4. YOLOv8 has idleness values between 35% and 42%, whereas YOLOv4 ranges from 65% to 73%, highlighting their effectiveness contrast. These lower rates for YOLOv8 demonstrate altogether diminished inactivity and speedier handling times over all information focuses.

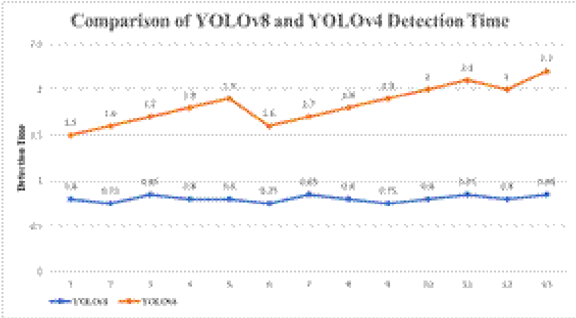

Fig. 5. Variation in Model Detection time Across Cases

Fig. 5. YOLOv8 illustrates a location time reliably around 0.8 seconds, whereas YOLOv4 vacillates between generally 1.5 and 2.2 seconds. This appears YOLOv8 accomplishes an essentially lower location time, around 47%–53% of YOLOv4's time, showing quicker question discovery over all trials.

DISCUSSION

The novel YOLOv8 fire detection model demonstrates significantly better performance than YOLOv4 across key metrics, including accuracy, error rate, and detection time, within the evaluation range of the dataset. Using independent sample T-tests, YOLOv8 showed an improvement in accuracy, achieving up to 97.20% compared to YOLOv4's best of 88.50%. Furthermore, YOLOv8 exhibited a lower error rate, achieving values as low as 0.34, compared to 0.73 in YOLOv4. The detection time was also reduced, with YOLOv8 taking a minimum of 0.75 seconds, as compared to YOLOv4's lowest value of 1.50 seconds. These results indicate that YOLOv8 significantly outperforms YOLOv4 in terms of both accuracy and speed, showcasing a more efficient fire detection capability when compared with prior studies."

The selection of anchor-free models like YOLOx and ExtremeNet, which perform superior in terms of precision and computational proficiency than more ordinary anchor-based procedures like YOLOv3 and Faster-RCNN, is one case of how this think about highlights the progressions in weapon location,[5].With the highest mAP of 0.905, YOLOx with CSPDarknet53 demonstrated its superiority in object detection for X-ray baggage screening. Furthermore, by adjusting to real-time threat changes, a novel "time sampling dynamic weapon assignment model" that uses reinforcement learning enhances decision-making. Wavelet transforms, a machine learning-based fault detection technique, guarantee power system dependability in the context of all-electric warships. Furthermore, even in blurry images, weapon detection in surveillance footage is improved by combining Mask RCNN with Gaussian deblur techniques, [13]. These developments highlight the increasing dependence on YOLOv8 and associated models for accurate, real-time firearm detection in a range of security applications. These technologies have the potential to enhance security response systems and public safety

The confinements of this framework incorporate its reliance on high-quality preparing information and computational assets required for real-time gun location. Outside variables like lighting varieties and protest situating may impact execution amid discovery , [15].

The limitations of this framework include its reliance on high-quality training data and the computational resources required for real-time firearm detection. External factors such as variations in lighting conditions and object positioning may impact detection performance. Due to its enhanced accuracy, speed, and adaptability, the proposed YOLOv8-based system can be extended to various security and law enforcement applications. The system is well-suited for surveillance, threat detection, and automated security monitoring. In future studies, optimization of YOLOv8's architecture and advanced deep learning techniques may be employed to address challenges such as environmental variability and computational overhead, further strengthening the system's scalability and effectiveness.

CONCLUSION

The YOLOv8 deep learning-based firearm detection system was designed and analyzed. The detection performance of the YOLOv8 model is significantly better than previous YOLO versions and alternative object detection algorithms. The YOLOv4 model achieves an accuracy ranging from 77.80% to 88.50%, while the YOLOv8 model demonstrates an enhanced accuracy of 94.80% to 98.00% in firearm detection across various settings. The standard deviation obtained for YOLOv4 accuracy is 3.37, whereas the standard deviation for YOLOv8 accuracy is 1.15, highlighting the improved consistency and reliability of YOLOv8.

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