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AN EFFICIENT DEEP LEARNING BASED FIREARM DETECTION SYSTEM USING YOLOV8

Submitted by

BOOMIKA K	**(73152121012)**
DEVADHARSHINI M	**(73152121019)**
RAMSURYA J	**(73152121046)**

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TIRUCHENGODE – 637 215

ANNA UNIVERSITY: CHENNAI 600 025

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K.S.R COLLEGE OF ENGINEERING

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TIRUCHENGODE – 637 215

ANNA UNIVERSITY: CHENNAI 600 025

BONAFIDE CERTIFICATE

Certified that this project report **“An Efficient Deep Learning Based Firearm Detection System Using Yolov8**” is the Bonafide work of **“BOOMIKA K (73152121012), DEVADHARSHINI M (73152121019), RAMSURYA J (73152121046)”** who carried out the project work under my supervision.

SIGNATURE	**SIGNATURE**
Dr. S. ANGURAJ, M.E., Ph.D.,	Dr. S.R. MENAKA, M.E., Ph.D.,
HEAD OF THE DEPARTMENT,	**SUPERVISOR,**
Assistant Professor,	Assistant Professor,
Department of IT,	Department of IT,
K.S.R. College of Engineering,	K.S.R. College of Engineering,
Tiruchengode - 637 215.	Tiruchengode - 637 215.

Submitted for the project viva-voce examination held on ______________

Internal Examiner **External Examiner**

DECLARATION

We affirm that the project work titled **"An Efficient Deep Learning Based Firearm Detection System Using Yolov8"** is being submitted in partial fulfilment for the award of "**BACHELOR OF TECHNOLOGY IN INFORMATION TECHNOLOGY**" the original work carried out by us. It has not formed the part of any other project work submitted for the award of any degree or diploma, either in this or any other University.

BOOMIKA K
(73152121012)

DEVADHARSHINI M
(73152121019)

RAMSURYA J
(73152121046)

I certify that the declaration made above by the candidates are true.

SIGNATURE OF THE SUPERVISOR
Dr. S.R. MENAKA, M.E., Ph.D.,
ASSISTANT PROFESSOR,
DEPARTMENT OF IT,
K.S.R. COLLEGE OF ENGINEERING,
TIRUCHENGODE - 637 -215.

Cognifyz

cognifyztechnologies@gmail.com

PROJECT COMPLETION CERTIFICATE

This certificate is presented to

K.S.R. COLLEGE OF ENGINEERING FINAL YEAR B. TECH (INFORMATION TECHNOLOGY) STUDENTS **Mr. RAMSURYA J, Ms. BOOMIKA K, & Ms. DEVADHARSHINI M** HAVE BEEN GIVEN PERMISSION TO WORK ON THEIR PROJECT, **"AN EFFICIENT DEEP LEARNING-BASED FIREARM DETECTION SYSTEM USING YOLOV8"** IN OUR RESPECTED ORGANIZATION.

DURING THE PERIOD FROM **DECEMBER 2024 TO MARCH 2025.**

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K.S.R. COLLEGE OF ENGINEERING (Autonomous)

(An Autonomous Institution, Approved by AICTE, Accredited by NAAC with 'A++' grade & Affiliated to Anna University)

K.S.R. Kalvi Nagar, Tiruchengode – 637 215, Namakkal District, Tamil Nadu.

Phone: 04288-274213 Fax: 04288-274757 E - mail: principal@ksrce.ac.in

DEPARTMENT OF INFORMATION TECHNOLOGY

BATCH: 2021 - 2025 **ACADEMIC YEAR: 2024 – 2025**

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Signature of the Supervisor **Programme Coordinator** **Head of the Department** **Principal**

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BOOIMKA K **DEVADHARSHINI M** **RAMSURYA J**

ABSTRACT

Firearm detection plays a crucial role in ensuring public safety, particularly in sensitive areas such as schools, airports, and public gatherings. The study compares two firearm detection models: YOLOv4 and YOLOv8. The YOLOv4-based system, tested across 26 models with varying detection thresholds, focuses on evaluating key parameters such as accuracy, latency, and detection time. The proposed YOLOv8 model leverages a public dataset to enhance real-time detection accuracy and efficiency. Experimental results demonstrate that YOLOv8 significantly outperforms YOLOv4 in terms of detection speed, accuracy, and reliability. Specifically, YOLOv8 achieves a higher accuracy (94.80%–98.00%) and a lower error rate (0.34–0.41) compared to YOLOv4’s accuracy range of 77.80%–88.50% and error rate of 0.65–0.73. Additionally, YOLOv8 reduces detection time to 1.50–2.20 seconds. These findings emphasize YOLOv8's potential to enhance firearm detection systems, contributing to improved security and public safety measures.

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ACRONYMS		ABBREVIATION
DL	-	Deep Learning
YOLO	-	You Only Look Once
CCTV	-	Closed-Circuit Television
MAP	-	Mean Average Precision
GPU	-	Graphics Processing Unit
RAM	-	Random Access Memory
SSD	-	Solid State Drive
ANN	-	Artificial Neural Network
CNN	-	Convolutional Neural Network
FPS	-	Frame Per Second
HDD	-	Hard Disk Drive

CHAPTER 1

INTRODUCTION

1.1 DEEP LEARNING

Deep learning is a branch of machine learning that enables computers to learn patterns from data using artificial neural networks (ANNs). Unlike traditional models, it does not require manual feature extraction but instead learns representations automatically. These models consist of multiple layers that process information hierarchically, improving accuracy over time. Deep learning is widely used for image recognition, natural language processing, and real-time object detection.

One of the most impactful applications of deep learning is in security systems, where it enhances surveillance, anomaly detection, and firearm detection. By leveraging deep learning, modern security technologies can identify threats with greater accuracy and faster response times. Convolutional Neural Networks (CNNs), a popular deep learning architecture, are particularly effective in image and video-based security applications. This allows security systems to detect weapons, recognize faces, and monitor suspicious activities automatically.

With ongoing advancements, deep learning is expected to further revolutionize real-time security, intelligent monitoring, and automated threat detection. As the technology matures, it will enable faster, more efficient, and smarter security systems for public and private safety. Future developments will focus on improving accuracy, reducing computational requirements, and making.

1.1.1 Key Components of Deep Learning

Deep learning models consist of multiple layers that process data in a hierarchical manner. The main components include:

- **Neurons:** The basic units of artificial neural networks that process inputs and generate outputs.
- **Layers:** Stacked groups of neurons, including:
  - **Input Layer:** Takes raw data as input.
  - **Hidden Layers:** Process and extract features from data.
  - **Output Layer:** Produces the final prediction or classification.
- **Weights and Biases:** Adjustable parameters that influence the network's learning process.

1.1.2 Types of Deep Learning Architectures

Deep learning encompasses several architectures designed for different applications:

- **Convolutional Neural Networks (CNNs**): Used for image recognition and object detection.
- **Recurrent Neural Networks (RNNs):** Designed for sequential data like speech and time-series analysis.
- **Transformer Models:** Used in NLP tasks, such as GPT and BERT.
- **Generative Adversarial Networks (GANs):** Used for image generation and enhancement.

1.1.3 Applications of Deep Learning

Deep learning has transformed various industries, including:

- **Healthcare:** Disease diagnosis, medical imaging, drug discovery.
- **Autonomous Vehicles:** Object detection, lane recognition, and decision-making.
- **Security Systems:** Facial recognition, anomaly detection, firearm detection.
- **Finance:** Fraud detection, risk assessment, stock market predictions.

1.2 FIREARM DETECTION

Firearm detection is a critical security measure aimed at identifying weapons in real-time using surveillance systems, machine learning, and deep learning models. With the rising incidents of gun violence in public spaces, automated firearm detection has become essential for preventing threats and ensuring public safety. Traditional security systems, which rely heavily on human intervention, often face limitations in terms of accuracy and response time. In contrast, AI-powered firearm detection systems offer real-time identification, enabling faster and more efficient threat mitigation.

1.2.1 Importance of Firearm Detection

The implementation of firearm detection systems plays a vital role in public safety and crime prevention. These systems help:

- **Enhance Security:** By detecting firearms in public places such as airports, schools, and shopping malls, security personnel can take immediate action.

- **Reduce Response Time:** Real-time firearm detection enables instant alerts, allowing law enforcement agencies to respond quickly.
- **Prevent Mass Casualties:** Automated systems minimize the risk of mass shootings by identifying threats early.
- **Assist Law Enforcement:** Firearm detection technology helps gather visual evidence for criminal investigations.

1.2.2 Applications of Firearm Detection

Firearm detection is widely used in various sectors, including:

- **Surveillance Cameras:** Automated firearm detection systems are integrated with CCTV cameras to monitor public spaces. These systems use deep learning models like YOLOv8 to identify firearms instantly.
- **Law Enforcement:** Police and security agencies use firearm detection to identify illegal weapon possession in real-time, enhancing public safety.
- **Smart Cities:** Automated firearm detection systems are employed in smart cities to track and prevent violence by integrating with public surveillance networks.
- **Military and Defence:** In defence applications, firearm detection is used to monitor restricted zones, detect illegal weapons, and prevent potential threats.
- **Retail and Private Security:** Shopping malls, banks, and private organizations deploy firearm detection systems to ensure customer and employee safety.

1.2.3 Technology Behind Firearm Detection

Modern firearm detection systems rely on deep learning models like YOLOv8, Faster R-CNN, and SSD. These models process live video feeds in real-time, identifying firearms with high accuracy.

- **Real-Time Processing:** The system processes multiple video frames per second, ensuring minimal latency in detection.
- **Bounding Box Detection:** The model draws bounding boxes around detected firearms and labels them accordingly.
- **Automated Alerts:** Upon detection, the system sends instant alerts to security personnel, enabling rapid intervention.

1.2.4 Challenges In Firearm Detection

Despite its benefits, firearm detection faces certain challenges:

- **False Positives:** Everyday objects (e.g., tools or mobile devices) can sometimes be misclassified as firearms**.**
- **Occlusions and Low Visibility:** Partial or hidden firearms are harder to detect, reducing the system’s accuracy.
- **Environmental Factors:** Low lighting, shadows, and crowded spaces can affect detection precision.

1.3 SECURITY SYSTEMS

A security system is a combination of technologies, protocols, and devices designed to protect individuals, property, and data from unauthorized access, theft, and potential threats. These systems play a vital role in safeguarding public and private spaces by detecting, preventing, and responding to security breaches. With advancements in technology, modern security systems incorporate AI-powered surveillance, real-time monitoring, and automated alerts, making them more efficient and reliable.

1.3.1 Components of Security Systems

- **Surveillance Cameras:** Used for continuous monitoring of specific areas, capturing video footage for real-time or post-event analysis.
- **Access Control Systems:** Regulate and restrict entry to authorized individuals using methods like keycards, biometrics, or PIN codes.
- **Fire and Smoke Alarms:** Trigger alerts in case of fire hazards, zensuring timely evacuation.
- **Alarm Systems:** Sound alerts or send notifications to security personnel upon detecting potential threats.
- **Web Application Firewalls (WAFs):** In cybersecurity, WAFs prevent SQL injection attacks, data breaches, and hacking attempts.

1.3.2 Importance of Security Systems

- **Crime Prevention:** Continuous surveillance and access controls help prevent theft, vandalism, and unauthorized access.
- **Real-Time Monitoring:** Advanced systems provide 24/7 live video **feeds** for immediate threat detection and response.
- **Workplace Safety:** In industrial and commercial settings, security systems protect employees and equipment from potential hazards.

1.3.3 Applications of Security Systems

Security systems are widely used across various sectors, including:

- **Residential Security:** Home security systems include CCTV cameras, alarms, and smart locks to prevent burglaries.
- **Commercial and Industrial Security:** Factories and warehouses use surveillance cameras and access controls to protect assets and monitor employee activities.
- **Public Safety:** Government agencies implement security systems in airports, metro stations, and public events to prevent potential threats.
- **Cybersecurity:** Firewalls, encryption, and intrusion detection systems (IDS) protect networks from unauthorized access and data breaches.

1.3.4 Challenges in Security Systems

- **False Alarms:** Motion sensors and cameras may sometimes trigger false positives, leading to unnecessary alerts.
- **Privacy Concerns:** Continuous surveillance may raise privacy issues, especially in public areas.
- **System Vulnerabilities:** Outdated or poorly configured security systems are prone to cyberattacks.
- **Maintenance and Costs:** Ensuring regular system maintenance and upgrading equipment requires significant investment.

1.4 ADVANTAGES

- **Enhanced Security:** Detecting SQLi attacks early helps prevent unauthorized access to databases.
- **Protection of Sensitive Data:** Ensures that user credentials, financial records, and personal information remain secure.
- **Improved System Reliability:** Prevents database corruption or unauthorized modifications that could disrupt services.
- **Automated Threat Detection:** Advanced AI-based techniques reduce the need for manual intervention in monitoring database security.

1.5 LIMITATIONS

- **False Positives and False Negatives:** Detection systems may sometimes misclassify legitimate queries as attacks or fail to detect sophisticated SQLi attempts.
- **Dependency on Updates:** Signature-based and ML-based detection methods require frequent updates to stay effective against evolving attack techniques.
- **Complex Implementation:** Integrating advanced SQLi detection systems into legacy applications can be challenging and resource intensive.

CHAPTER 2

LITERATURE REVIEW

2.1 WEAPON TARGET ALLOCATION USING GA-APSO ALGORITHM

Xu Qiang-Qiang et.al. (2024), addressed the Weapon Target Allocation (WTA) problem, a complex combinatorial optimization challenge in defence strategy, aiming to optimize the allocation of limited weapons to various targets to maximize combat effectiveness. Due to the NP-hard nature of this problem, the study introduces an improved Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) hybrid, named GA-APSO. This approach integrates chaotic initialization techniques and adaptive parameter adjustments to enhance global search capability and computational efficiency. Experimental validation shows that GA-APSO surpasses traditional PSO, GA, and hybrid GA-PSO models in stability, optimization performance, and solution accuracy. The study evaluates the algorithm’s performance on static WTA problems and its scalability in large-scale scenarios, confirming its reliability for real-world battlefield applications.

2.2 ANCHOR-FREE WEAPON DETECTION IN X-RAY BAGGAGE SECURITY SCREENING

Shuai Li. et al. (2023) proposed an anchor-free convolutional neural network (CNN) approach for detecting weapons, such as knives and handguns, in X-ray baggage security images. Traditional anchor-based object detection methods suffer from computational complexity and class imbalance issues, which this study aims to overcome by eliminating the need for predefined anchor boxes. Six anchor-free models (CornerNet, CenterNet, CornerNet-Lite, ExtremeNet, Objects as Points, and YOLOx) are compared against anchor-based models (Faster-RCNN, YOLOv3, YOLOv5). Experimental results indicate that YOLOx with CSPDarknet53 achieves a mean average precision (mAP) of 0.905, while ExtremeNet with Hourglass-104 reaches 0.900, outperforming anchor-based methods. The findings highlight the practical effectiveness of anchor-free methods for real-time security screening.

2.3 A TIME-DRIVEN DYNAMIC WEAPON TARGET ASSIGNMENT METHOD

Chang Liu. et al. (2023) critiqued the traditional dynamic WTA models, which rely on sequential static assignments without considering real-time changes in threat rankings a time sampling dynamic weapon assignment model" that partitions decision-making stages using predefined time intervals to capture evolving target threat levels. A reinforcement learning-based assignment method is developed and tested against traditional heuristic algorithms. Comparative simulations demonstrate that the reinforcement learning model offers superior decision-making timeliness and comprehensive threat assessment, making it a more effective approach for dynamic battlefield environments.

2.4 SC-LITE: A LIGHTWEIGHT MODEL FOR REAL-TIME X-RAY SECURITY CHECKS

Han Li. et al. (2024) proposed SC-Lite, an optimized deep learning model for real-time X-ray security inspections, designed to enhance detection accuracy while reducing computational complexity. The model is based on YOLOv8 and incorporates the CSPNet Faster Convolution Network Module (C2F_FM) for memory-efficient processing and the Adaptation-BiFPN module for improved multi-scale feature fusion. Additionally, the LAMP pruning strategy is applied to minimize architectural complexity. Experimental results indicate that SC-Lite outperforms existing models in all metrics, achieving a mean average precision (mAP) of 94.3% on the LSIray dataset and 94.8% on the OPIXray dataset while significantly improving frame rates, demonstrating its effectiveness for security-critical applications.

2.5 LOW-COST MILLIMETER WAVE FREQUENCY SCANNING FOR CONCEALED WEAPON DETECTION

Li Shichao Li. et al. (2022) introduced a low-cost Frequency Scanning-based Synthetic Aperture Radar (F-SAR) system for high-resolution imaging of concealed weapons. Unlike traditional multiple-input multiple-output (MIMO) array imaging, which requires complex channel switching, F-SAR utilizes a single-input single-output (SISO) configuration to reduce hardware costs and imaging time. The study presents a hybrid scanning model that combines frequency-controlled beam steering in cross-track with mechanical scanning in along-track. Chamber experiments verify the scanning range (23°) and resolution (5 mm in both dimensions), while real-world trials confirm the effectiveness of through-clothes imaging for detecting concealed objects. This research highlights F-SAR’s potential for security screening applications.

2.6 WEAPON DETECTION IN REAL-TIME CCTV VIDEOS USING DEEP LEARNING

Muhammad Tahir Bhatti et al. (2021) addressed the challenge of real-time weapon detection in CCTV surveillance. While modern deep learning algorithms and advanced CCTV cameras have enhanced surveillance, real-time firearm detection remains difficult due to angle variations, occlusions, and environmental factors. The study proposes a system that applies deep learning models such as VGG16, Inception-V3, Inception-ResNetV2, SSD MobileNetV1, Faster-RCNN Inception-ResNetV2 (FRIRv2), YOLOv3, and YOLOv4. Among these, YOLOv4 achieved the highest F1-score of 91% and a mean average precision of 91.73%. The study also highlights the need for a dedicated dataset, leading the authors to construct a comprehensive dataset sourced from personal collections, the University of Granada, GitHub repositories, and Internet Movies Firearms Database (IMFDB).

2.7 HAWK-EYE: AN AI-POWERED THREAT DETECTOR FOR INTELLIGENT SURVEILLANCE CAMERAS

Ahmed Abdelmoamen Ahmed et al. (2021) introduced "Hawk-Eye," a real-time AI-driven surveillance system designed to detect weapons, masked faces, and suspicious objects. The system utilizes Mask R-CNN for high-quality segmentation and classification of detected threats. Hawk-Eye is designed to operate on both edge devices, such as Raspberry Pi with Intel Neural Compute Stick 2, and cloud-based servers, ensuring scalability and real-time threat response. The system achieves a high detection accuracy of 94% and integrates motion detection to enhance surveillance efficiency. The study demonstrates how AI-powered threat detection can significantly improve security measures in high-risk environments such as schools and public spaces.

2.8 VIDEO SURVEILLANCE ANOMALY DETECTION: A REVIEW ON DEEP LEARNING BENCHMARK

Duja Kashaf U et al. (2024) provided an extensive review of deep learning methodologies in video surveillance anomaly detection (VSAD). The study discusses the computational challenges posed by large-scale datasets and the need for real-time monitoring. Various deep learning approaches, including CNNs, transformer models, YOLO, and autoencoders, are explored for their efficiency in handling time-series data and real-time analysis. Despite advancements, the authors emphasize that current VSAD techniques still lack a definitive solution for real-time large-scale anomaly detection, necessitating further research to enhance accuracy and computational efficiency.

2.9 ENHANCED ANOMALY DETECTION IN PANDEMIC SURVEILLANCE VIDEOS: AN ATTENTION APPROACH WITH EFFICIENTNET-B0 AND CBAM INTEGRATION

Amin Sareer Ul et al. (2024) proposed a surveillance system designed to detect anomalous behaviors related to public health violations, such as incorrect mask usage, sneezing, and spitting. The system integrates EfficientNet-B0 with Convolutional Block Attention Module (CBAM) to enhance feature extraction and classification performance. By replacing the Squeeze-and-Excitation (SE) module with CBAM, the model achieves an accuracy boost from 87% to 96%. The study highlights the effectiveness of attention-based deep learning models in refining real-time anomaly detection.

2.10 ENHANCED ANOMALY DETECTION IN PANDEMIC SURVEILLANCE VIDEOS: AN ATTENTION APPROACH WITH EFFICIENTNET-B0 AND CBAM INTEGRATION

Yuan Wen (2024) presented an improved CNN-based deep learning model for behavior recognition in surveillance videos while addressing privacy concerns. The model incorporates multi-scale feature fusion, spatiotemporal attention mechanisms, and LSTMs to achieve an accuracy of 95.8% on the UCF-101 dataset. Additionally, the study proposes data anonymization, encrypted transmission, and access control measures to enhance privacy protection. Experimental results indicate a 40% increase in data processing time due to privacy measures but only a 2.5% drop in model performance, demonstrating a viable balance between security and efficiency.

2.11 YOLO-ESCA: A HIGH-PERFORMANCE SAFETY HELMET STANDARD WEARING BEHAVIOR DETECTION MODEL

Jin Peijian et al. (2024) introduced YOLO-ESCA, an improved YOLOv5-based model for detecting proper helmet usage among workers. By integrating Efficient Intersection over Union loss function (EIOU-loss), Soft-NMS, and CBAM, the model achieves a mean average precision (mAP) of 94.7% and an FPS of 65.3. The study demonstrates the effectiveness of real-time object detection models in occupational safety monitoring and proposes improvements for small-object detection in challenging environments.

2.12 REALTIME CROWD MONITORING—ESTIMATING COUNT, SPEED, AND DIRECTION USING HYBRIDIZED YOLOV4

Muhammad Haris Kaka Khe l et al. (2023) proposed a Hybrid YOLOv4 model for real-time crowd monitoring, estimating crowd size, movement speed, and direction. The model integrates pruning techniques and convolutional attention mechanisms to improve computational efficiency, achieving a 33% increase in accuracy and a mean average precision (mAP) of 92.1%. The research is particularly relevant for managing crowd safety in public spaces and preventing stampedes or overcrowding incidents.

2.13 PUBLICVISION: A SECURE SMART SURVEILLANCE SYSTEM FOR CROWD BEHAVIOR RECOGNITION.

Almiqdad Elzein et al. (2024) introduced "PublicVision," a surveillance system designed for real-time crowd behavior analysis. The system employs a Swin Transformer-based deep learning model to classify crowd behaviors based on size and violence levels. It ensures secure data transmission through a Dynamic Multipoint Virtual Private Network (DMVPN) with IP Security (IPSec) and firewall integration. Real-time inference using DeepStream SDK demonstrates significant improvements in public safety monitoring and security.

2.14 STABILIZED ADAPTIVE SAMPLING CONTROL FOR RELIABLE REAL-TIME LEARNING BASED SURVEILLANCE SYSTEMS

Kim Dohyun et al. (2021) presented a dynamic sampling rate adaptation algorithm for real-time computer vision surveillance systems. The study addresses computational resource limitations in CCTV-based monitoring by optimizing image sampling rates to prevent queue overflow while maximizing object recognition accuracy. The proposed Lyapunov optimization framework significantly improves real-time deep learning performance in IoT-connected surveillance environments.

2.15 WEAPON DETECTION USING YOLOV4 AND CNN

Atharv Belurkar et al. (2022) presented a weapon detection system that leverages YOLOv4 for object detection, enabling automatic firearm and knife recognition in CCTV footage. The system notifies operators via email, including an image and location details. The approach enhances city security with minimal human intervention.

2.16 A DEEP LEARNING-BASED EFFICIENT FIREARMS MONITORING TECHNIQUE FOR SECURE SMART

Chatterjee Rajdeep et al. (2023) introduced an ensemble-based firearm detection system using Faster R-CNN and EfficientDet architectures. The model applies Non-Maximum Suppression and Weighted Boxes Fusion for improved gun and face detection. Achieving a mean average precision of 77.02%, the system is effective for real-time surveillance and social media content analysis.

2.17 A DEEP LEARNING-BASED EFFICIENT FIREARMS MONITORING TECHNIQUE FOR BUILDING SECURE SMART

Ahmed Abdullah A. Shareef et al. (2023) proposed a real-time surveillance model for firearm and fire detection using YOLOv5. The system processes video frames efficiently to detect threats and generate alerts. Experimental results show a high-speed detection rate, making it suitable for emergency response scenarios.

2.18 WEAPON-TARGET ASSIGNMENT STRATEGY IN JOINT COMBAT DECISION-MAKING BASED ON MULTI-HEAD DEEP REINFORCEMENT LEARNING

Li Shuai et al. (2023) presented a reinforcement learning-based framework (RL4WTA) to optimize weapon-target assignment in combat scenarios. Using a multi-head Q-value network and Markov Decision Process (MDP), the model enhances decision-making efficiency, outperforming traditional optimization techniques.

2.19 HANDGUN DETECTION USING HUMAN POSE AND WEAPON APPEARANCE

Jesus Ruiz-Santaquiteria et al. (2021) developed a handgun detection framework that combines visual weapon appearance with human pose estimation. By processing pose keypoints and weapon features in separate subnetworks, the model improves firearm detection accuracy, outperforming previous approaches by 4.23 to 18.9 AP points.

2.20 WEAPONS DETECTION FOR SECURITY AND VIDEO SURVEILLANCE USING CNN AND YOLO-V5S

Abdul Hanan Ashraf et al. (2021) proposed an automated firearm detection framework using YOLOv5 and an Area of Interest (AOI) method to minimize false positives and false negatives. The system achieves a fast detection rate of 0.010s per frame, significantly outperforming Faster R-CNN (0.17s per frame).

2.21 IMPROVING ARMED PEOPLE DETECTION ON VIDEO SURVEILLANCE THROUGH HEURISTICS AND MACHINE LEARNING MODELS

Alonso Javier Amado-Garfias et al. (2024) introduced a YOLOv4-based system for detecting firearms and identifying armed individuals in surveillance videos. Using heuristics and machine learning models like Random Forest and Gradient Boosting, the approach achieves an accuracy of 85.44% with an F1-score of 87.87%.

2.22 R-CNN AND YOLOV4 BASED DEEP LEARNING MODEL FOR INTELLIGENT DETECTION OF WEAPONRIES IN REAL TIME VIDEO

K.P. Vijayakumar et al. (2023) developed a firearm detection system utilizing a custom dataset of five weapon types. YOLOv4 achieves a mean Average Precision (mAP) of 96.04% at 19 FPS on a GeForce MX250 GPU, outperforming R-CNN's 71% accuracy. The system ensures high-accuracy surveillance monitoring.

2.23 DEEP LEARNING-BASED WEAPON DETECTION USING LIVE CAMERAS

Abhinav Bhardwa (2022) presented a firearm detection system utilizing CNN-based classification and TensorFlow 2's pre-trained models. A new dataset of 411 images enhances detection accuracy, achieving 71.8% accuracy on SSD MobileNet V2 FPNLite 640x640. The system performs robustly in varied lighting conditions.

2.24 OBJECT DETECTION METHOD USING IMAGE AND NUMBER OF OBJECTS ON IMAGE AS LABEL

Keong-Hun Choi et al. (2024) proposed a novel object detection algorithm that eliminates the need for bounding box labels. Using reinforcement learning with an actor-critic framework, the system achieves comparable performance to transformer-based models while improving adaptability in unseen environments .

2.25 DETECTION OF ABANDONED AND STOLEN OBJECTS BASED ON DUAL BACKGROUND MODEL AND MASK R-CNN

Hyeseung Park et al. (2021) presented an efficient method for distinguishing abandoned objects, stolen objects, and ghost regions in video surveillance systems. The approach integrates a dual background model for detecting stationary objects and Mask R-CNN for object segmentation. By analyzing whether a segmented object exists in the current or past video frame, the system accurately classifies stationary objects. The method effectively reduces false positives caused by shadows and lighting changes. Experimental results demonstrate the system's reliability, making it suitable for public security applications in environments where traditional intrusion detection systems are ineffective.

Table 2.1 Comparison of Various Algorithm Used in YOLOv8

S. No	Title	Authors	Algorithm	Advantages	Disadvantages
1	Weapon Target Allocation Using GA-APSO Algorithm	Xu Qiang-Qiang et al.	GA-APSO (Genetic Algorithm + Adaptive PSO)	Improved optimization and solution accuracy	Computationally intensive
2	Anchor-Free Weapon Detection in X-Ray Baggage Security Screening	Shuai Li et al.	YOLOx, CornerNet, CenterNet	Eliminates anchor-based limitations, high mAP	Requires large datasets
3	A Time-Driven Dynamic Weapon Target Assignment Method	Chang Liu et al.	Reinforcement Learning	Real-time adaptability	High training complexity
4	SC-Lite: A Lightweight Model for Real-Time X-	Han Li et al.	YOLOv8 + CSPNet + BiFPN	High accuracy with low computational	Limited generalization

	Ray Security Checks			cost	
5	Low-Cost Millimeter Wave Frequency Scanning for Concealed Weapon Detection	Li Shichao et al.	F-SAR (Frequency Scanning Synthetic Aperture Radar)	Low-cost and efficient	Limited scanning range
6	Weapon Detection in Real-Time CCTV Videos Using Deep Learning	Muhammad Tahir Bhatti et al.	YOLOv4, Faster-RCNN, SSD MobileNet	High F1-score, real-time performance	Sensitive to occlusions
7	Hawk-Eye: An AI-Powered Threat Detector for Intelligent Surveillance Cameras	Ahmed Abdelmoamen Ahmed et al.	Mask R-CNN	High segmentation accuracy	Requires significant processing power
8	Video Surveillance	Duja	CNN, YOLO,	Comprehensive	Lack of a definitive

	Anomaly Detection: A Review on Deep Learning Benchmark	Kashaf U et al.	Transformers	analysis of VSAD techniques	real-time solution
9	Enhanced Anomaly Detection in Pandemic Surveillance Videos	Amin Sareer Ul et al.	EfficientNet-B0 + CBAM	Improved accuracy with attention mechanisms	Computational overhead
10	Enhancing Video Surveillance and Behavior Recognition While Ensuring Privacy Protection	Yuan Wen et al.	CNN + LSTM + Multi-scale Feature Fusion	High accuracy with privacy measures	Increased processing time
11	YOLO-ESCA: A High-Performance Safety Helmet	Jin Peijian et al.	YOLOv5 + EIOU-loss + Soft-NMS	High mAP and real-time efficiency	Small-object detection challenges

	Standard Wearing Behavior Detection Model				
12	Realtime Crowd Monitoring—Estimating Count, Speed, and Direction Using Hybridized YOLOv4	Muhammad Haris Kaka Khel et al.	YOLOv4 + Pruning + Attention	High accuracy in real-time monitoring	Computationally expensive
13	PublicVision: A Secure Smart Surveillance System for Crowd Behavior Recognition	Almiqdad Elzein et al.	Swin Transformer	Secure data transmission	High resource consumption
14	Stabilized Adaptive Sampling Control for Reliable Real-	Kim Dohyun et al.	Lyapunov Optimization	Maximizes object recognition accuracy	Limited to IoT applications

	Time Learning-Based Surveillance Systems				
15	Weapon Detection Using YOLOv4 and CNN	Atharv Belurkar et al.	YOLOv4	Automatic firearm detection	Requires dedicated dataset
16	A Deep Learning-Based Efficient Firearms Monitoring Technique for Secure Smart Systems	Chatterjee Rajdeep et al.	Faster R-CNN, EfficientDet	High mAP, real-time performance	High computational cost
17	A Deep Learning-Based Efficient Firearms Monitoring Technique for Building Secure	Ahmed Abdullah A. Shareef et al.	YOLOv5	High-speed detection rate	Potential false positives

	Smart				
18	Weapon-Target Assignment Strategy in Joint Combat Decision-Making	Li Shuai et al.	Multi-Head Deep Reinforcement Learning	Efficient decision-making	Requires large-scale training
19	Handgun Detection Using Human Pose and Weapon Appearance	Jesus Ruiz-Santaquiteria et al.	Pose Estimation + CNN	Improved detection accuracy	Complex model structure
20	Weapons Detection for Security and Video Surveillance Using CNN and YOLO-V5s	Abdul Hanan Ashraf et al.	YOLOv5 + AOI method	Fast detection rate	Sensitive to environmental factors
21	Improving Armed	Alonso	YOLOv4 +	High accuracy	Heuristic-based

	People Detection on Video Surveillance	Javier Amado-Garfias et al.	Machine Learning (Random Forest, Gradient Boosting)		limitations
22	R-CNN and YOLOV4 based Deep Learning Model for Intelligent Detection of Weaponries	K.P. Vijayakumar et al.	YOLOv4, R-CNN	High accuracy and FPS	Limited small-object detection
23	Deep Learning-Based Weapon Detection Using Live Cameras	Abhinav Bhardwa	CNN + TensorFlow 2	Robust performance in varying conditions	Moderate accuracy (71.8%)
24	Object Detection Method Using Image and Number	Keong-Hun Choi et al.	Reinforcement Learning + Actor-Critic	High adaptability	Requires extensive training

	of Objects on Image as Label				
25	Detection of Abandoned and Stolen Objects Based on Dual Background Model and Mask R-CNN	Hyeseung Park et al.	Dual Background Model + Mask R-CNN	High accuracy for security applications	Sensitive to lighting conditions

2.26 SUMMARY

The YOLOv8 model ensures automated and real-time detection with high accuracy, though challenges such as false positives and computational cost persist. Hybrid deep learning techniques, including CNN-LSTM and reinforcement learning, enhance detection accuracy while addressing data dependency and interpretability concerns. Post-processing methods like Non-Maximum Suppression (NMS) refine detections by eliminating duplicates and filtering low-confidence predictions. Additionally, alert systems and web-based dashboards provide real-time monitoring, improving security response and threat mitigation. These advancements contribute significantly to enhancing surveillance and security measures in firearm detection.

CHAPTER 3

RESEARCH GAP BETWEEN EXISTING AND PROPOSED SYSTEM

3.1 EXISTING SYSTEM

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 footage The 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.

3.2 DRAWBACKS OF EXISTING SYSTEM

The existing system has the following disadvantages:

- **Overfitting Risk:** Susceptible to overfitting, especially with unbalanced or noisy datasets.
- **High Computational Cost:** Requires significant processing power, limiting real-time efficiency.

- **Limited Generalization:** Struggles with complex environments, occlusions, and varying lighting conditions.

3.3 PROPOSED SYSTEM

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, the solution enhances public safety through rapid and reliable threat detection.

3.3.1 Data Collection and Preparation

The firearm detection dataset from Kaggle included diverse firearm images. Pre-processing ensured high-quality input for YOLOv8 training. Images were resized, normalized, and augmented for better robustness. Techniques like rotation, flipping, and brightness adjustments improved generalization. Duplicate and low-quality images were removed for dataset integrity.

3.3.2 Model Selection and Training (YOLOv8)

YOLOv8 was selected for firearm detection due to its real-time efficiency and accuracy. It was trained using transfer learning on a pre-processed dataset. Hyperparameters like learning rate, batch size, and anchor boxes were optimized. The dataset was split into training, validation, and testing for fair evaluation. Training across multiple epochs minimized loss and improved accuracy. Metrics like mAP and confidence scores were monitored to prevent overfitting.

3.3.3 Real-time Firearm Detection (Webcam/Live Feed)

The YOLOv8 model was integrated with a real-time camera system for firearm detection Live video frames were processed to detect and localize firearms with bounding boxes. The system's responsiveness enabled immediate action for security applications.

3.3.4 Alert System Integration

Firearm detection, the system triggered an alert with a notification and beep. Real-time alerts displayed detection confidence and location. A logging system recorded timestamps, images, and confidence scores. Security teams used logs to review detections and analyze trends. Stored data improved response strategies and threat assessment. The alert system ensured quick and effective threat response.

3.3.5 Deployment and Optimization

The firearm detection system was deployed for real-world security integration. The YOLOv8 model ran on an edge device or server for live video processing. Optimization techniques like model quantization and hardware acceleration improved speed. Continuous monitoring and retraining helped adapt to evolving threats. Periodic evaluations fine-tuned detection accuracy and resource efficiency.

CHAPTER 4

FIREARM DETECTION USING YOLOv8

4.1 INTRODUCTION OF FIREARM DETECTION SYSTEM

The firearm detection system follows a structured process using YOLOv8 to ensure efficient and accurate threat identification. Figure 4.1 insulated the Workflow of Firearm Detection and Secured Alert System. It begins by capturing input from a live camera or uploaded media, preprocessing frames to enhance detection accuracy. The YOLOv8 model is then applied to identify objects, distinguishing between firearms, knives, and non-threatening items. If a weapon is detected, the system logs the event, saves the detected frames and videos, and triggers an alert sound. The results are displayed on a web interface, providing real-time insights into potential threats. The streamlined methodology enhances security by ensuring timely and accurate firearm detection.

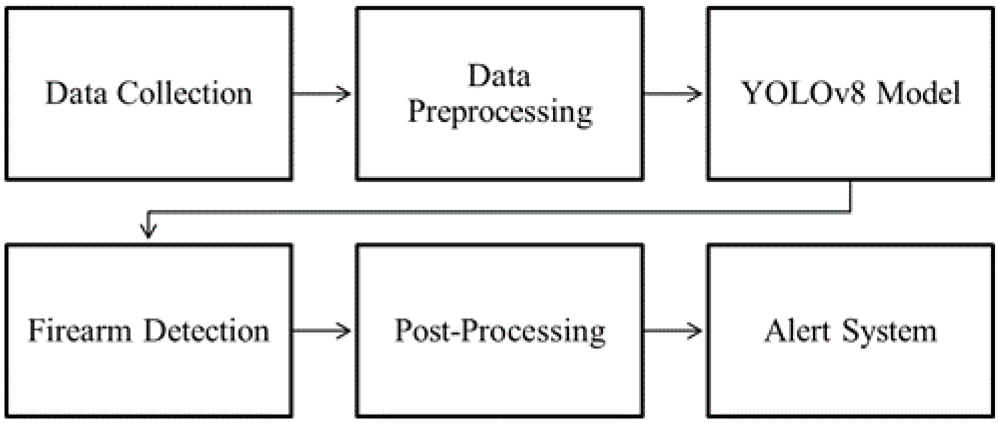

Figure 4.1 Firearm Detection and Secured Alert System Workflow

4.1.1 Data Collection

Data Collection is the first step in the firearm detection process. It involves gathering images and videos of firearms from sources like CCTV footage, public datasets, and manually captured media. To improve model accuracy, non-firearm images are also included to help differentiate between firearms and other objects. It ensures the model learns to reduce false detections and improve reliability. A well-curated dataset is essential for effective firearm detection using YOLOv8.

4.1.2 Data Pre-processing

Data preprocessing ensures consistency and accuracy before training the firearm detection model. Images and videos are resized and normalized for uniformity. Annotations using tools like Label Img or Robot flow help mark firearms. Data augmentation techniques like rotation, flipping, and brightness adjustments enhance robustness. These steps improve the model's generali station and real-world accuracy.

4.1.3 YOLOv8 Model

YOLOv8 model is the core component of the firearm detection system, where the pre-processed dataset is used to train a deep learning model for object detection. YOLOv8, an advanced version of the You Only Look Once (YOLO) series, is designed for high-speed and accurate real-time detection. During training, the model learns to detect firearms by extracting object features and assigning confidence scores to its predictions. It uses convolutional neural networks (CNNs) to analyse image data, identify key patterns, and differentiate firearms from other objects. With its optimized architecture, YOLOv8 ensures fast and precise detection, making it highly suitable for security and surveillance applications.

4.1.4 Firearm Detection

YOLOv8 model is successfully trained, it is deployed for real-time firearm detection in surveillance and security systems. The model continuously processes video frames from surveillance cameras**,** analysing each frame to identify firearms accurately. the model classifies objects in the video stream and determines whether a firearm is present. It assigns confidence scores to its predictions, ensuring that detections are both accurate and reliable**.** The step is crucial for enhancing security measures, allowing for rapid threat identification and immediate response in critical situations.

4.1.5 Post-Processing

The post-processing phase refines firearm detection for accuracy and reliability. Non-Maximum Suppression (NMS) removes duplicate detections, keeping the most confident ones. Confidence thresholding filters out low-confidence predictions. Detection details like time, location, and confidence scores are logged for analysis.

4.1.6 Alert System

Firearms are detected, the system immediately triggers an alert to ensure a swift response to potential threats. Upon detecting a firearm, the system triggers and immediate alert. Security personnel are notified via alarm, email, SMS, or a security platform. The alert ensures a swift response to potential threats. Detection data is logged for analysis and strategy improvement.

4.2 YOLOv8 ALGORITHM

Step 1: Collect and label firearm and non-firearm images to create a dataset.

Step 2: Preprocess the images by resizing, normalizing, and augmenting data for better model learning.

Step 3: Train the YOLOv8 model using the labeled dataset with appropriate hyperparameters (batch size, learning rate, etc.).

Step 4: Validate the trained model on a separate test dataset to evaluate performance (accuracy, precision, recall).

Step 5: Save the trained model for real-time inference**.**

Step 6: Capture real-time input from a webcam or video feed.

Step 7: Preprocess the input frame (resize, normalize) before feeding it into the YOLOv8 model.

Step 8: Apply the YOLOv8 object detection model to identify objects in the frame.

Step 9: Extract detected objects and classify them as "firearm" or "non-firearm".

Step 10: Use Non-Maximum Suppression (NMS) to remove duplicate detections and refine bounding boxes.

Step 11: If a firearm is detected, trigger an alert system:

i. Save detection logs (timestamp, object type, confidence score).

ii. Play an alert sound for security notification.

iii. Display the detection output on a web interface**.**

Step 12: If no firearm is detected, continue monitoring.

4.3 PSEUDO CODE

```
START

INITIALIZE camera feed (default or external)
LOAD YOLO model ("model.pt")
DEFINE class names (e.g., 'Firearm')
WHILE camera is active:
    CAPTURE a frame from the camera
    IF frame is not captured successfully:
            PRINT error message
            EXIT loop
    RESIZE frame to (640x480)
    RUN YOLO model on the frame to detect objects
    SET firearm_detected to FALSE
    FOR each detection in YOLO results:
        GET bounding box coordinates (x1, y1, x2, y2)
        GET confidence score
        CONVERT confidence score to percentage
        GET detected class
        IF confidence is greater than 40%:
            DRAW bounding box around the detected object
            DISPLAY detected class name on frame
            SET firearm_detected to TRUE
```

```
        SHOW the processed frame
        IF firearm_detected:
                PRINT "Firearm detected! Terminating the camera feed..."
                EXIT loop
        IF user presses 'q':
            PRINT "Exiting..."
       EXIT loop
RELEASE the camera resource
CLOSE all OpenCV windows
END
```

CHAPTER 5

RESULTS AND DISCUSSION

5.1 RESULT ANALYSIS

5.1.1 Home Page

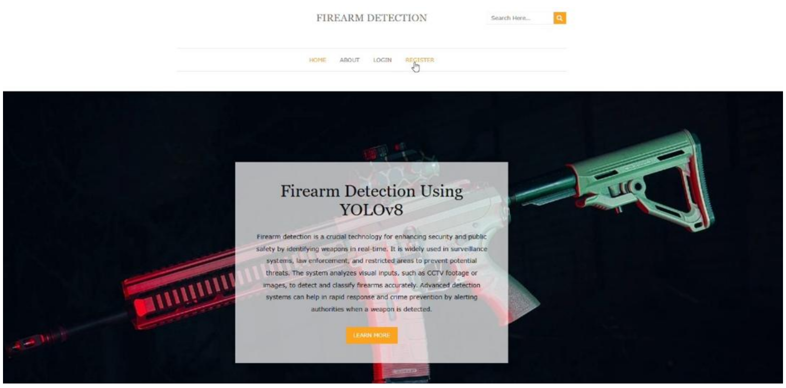

Figure 5.1 Home Page

Figure 5.1 insulated the home page of firearm detection it contains title, tagline, register, login page.

5.1.2 Registration Page

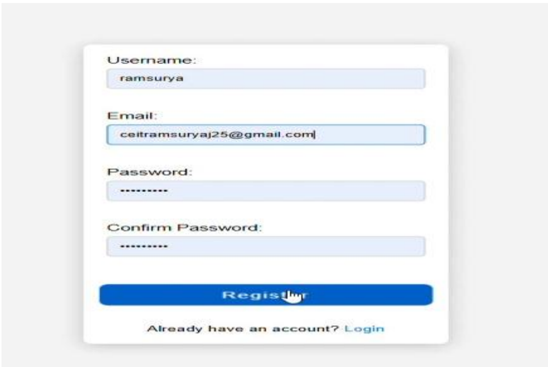

Figure 5.2 Registration Page for Account Creation

Figure 5.2 1 insulated the 2 Registration Page for Account Creation it contains several fields designed to capture the necessary user information like Username, Email, Password, confirm password The form also contains interactive buttons and links. The Register button is prominently displayed in blue with white text labeled "Register" and followed by Login page.

5.1.3 Login Page

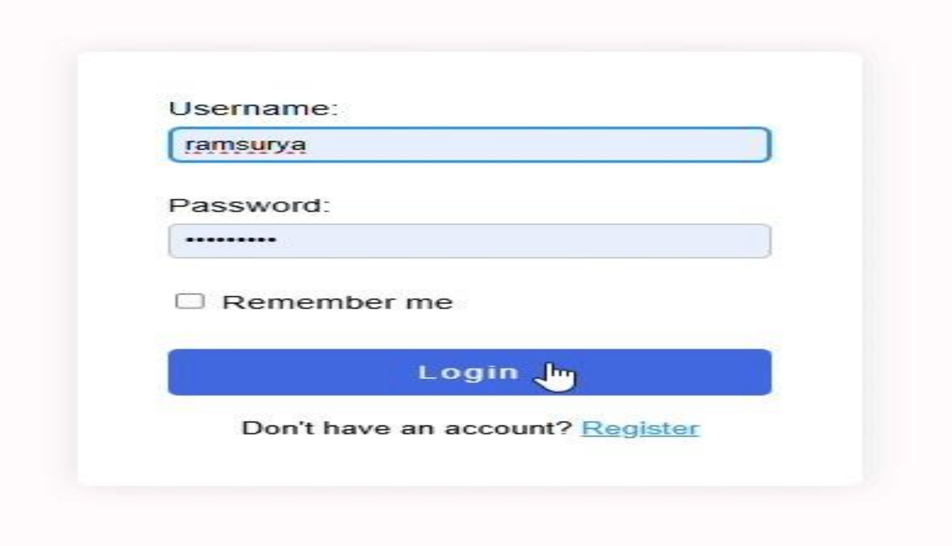

Figure 5.3 Login Page for Access Firearm Detection

Figure 5.3 insulated the Login Page for Access Firearm Detection. It contains images consisting of fields and interactive elements designed for user authentication

5.1.4 Live Camera Feed Activated

Figure 5.4 Live Camera Feed Activated for Detection

Figure 5.4 insulated the Live Camera Feed Activated for Detection. The interface features a clean and straightforward design with a centered "Start Camera" and "Stop Camera" button.

5.1.5 Object Detection and Alert

Figure 5.5 Object Detection and Alert

Figure 5.5 insulated the Object Detection and Alert The interface displays two buttons: "Start Camera" and "Stop Camera". the system detects a firearm and highlights it with bounding boxes labeled with "Gun" and confidence scores, indicating the accuracy of the detection. Above the video feed, a warning message "A Firearm Detected!"

5.2 COMPARISON OF ACCURAY, ERROR RATE AND DETECTION TIME

Table 5.1 COMPARISON BETWEEN YOLOv4 and YOLOv8

Test No	**Accuracy**		**Error Rate**		**Detection Time (s)**	
	Yolov4	Yolov8	Yolov4	Yolov8	Yolov4	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 table 5.1 compares YOLOv4 (existing) and YOLOv8 (proposed) in firearm detection based on Accuracy, Error Rate, and Detection Time. YOLOv8 outperforms YOLOv4 with higher accuracy (94.80%–98.00% vs. 77.80%–88.50%), lower error rate (0.34–0.41 vs. 0.65–0.73), and faster detection (0.75–0.85s vs. 1.50–2.20s).

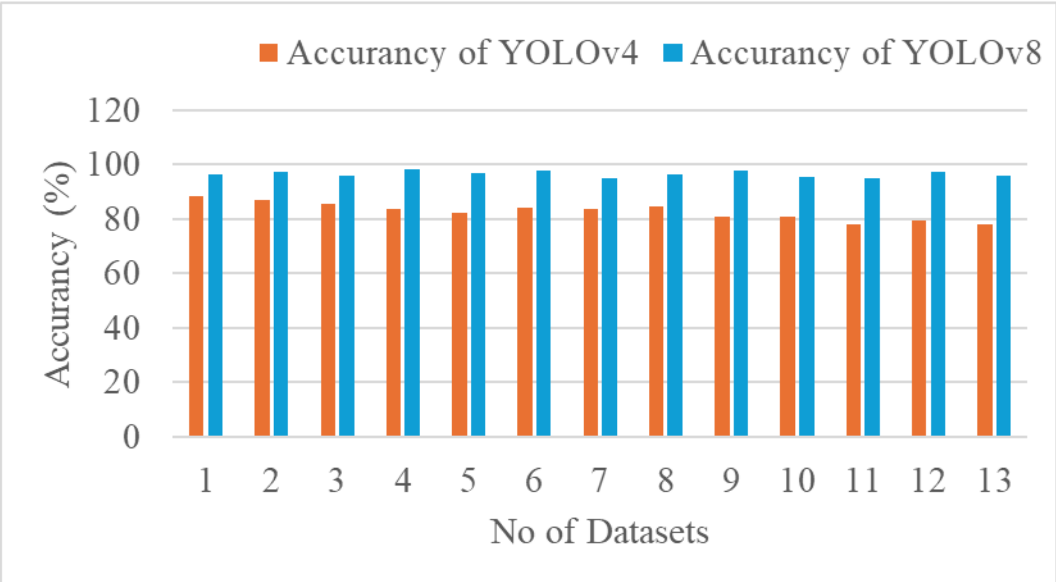

Figure 5.8 Accuracy of YOLOv4 and YOLOv8

The figure 5.8 represents the comparison of YOLOv8 and YOLOv4 consistently achieves higher accuracy than YOLOv4 across all datasets. The accuracy of YOLOv8 remains close to 100%, indicating its superior performance and reliability in firearm detection. In contrast, YOLOv4 shows lower accuracy, typically ranging between 80% and 90%, highlighting the improvements in the newer model.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

The firearm detection system using YOLOv8 represents a significant advancement in real-time security monitoring. By leveraging deep learning and advanced computer vision techniques, the system is capable of accurately detecting firearms in video feeds from surveillance cameras, ensuring enhanced public safety. The integration of efficient post-processing techniques, such as Non-Maximum Suppression and thresholding, helps reduce false positives, ensuring the system only alerts for legitimate threats. Additionally, the system’s ability to generate real-time text alerts provides security personnel with critical information, enabling them to respond quickly to potential threats. While challenges remain, such as managing occlusions and variations in lighting conditions, the system's performance—demonstrated by high precision and recalls its effectiveness in firearm detection. The project showcases the potential of deep learning in enhancing security measures and provides a reliable tool for detecting firearms in sensitive environments. As technology continues to improve, approach can be further refined and adapted to various real-world applications, offering increased safety and protection in public spaces.

6.2 FUTURE WORK

In the future, the firearm detection system can be enhanced in several ways to further improve its accuracy, efficiency, and overall effectiveness. One major area of development is the expansion of the model's capability to detect a wider range of weapons beyond firearms, such as knives or other dangerous objects. This would allow the system to identify and respond to various types of threats. Additionally, integrating advanced tracking algorithms could improve the system’s ability to monitor the movement of detected firearms across multiple video frames, enabling more precise identification of potential risks in real-time. Incorporating multi-camera systems could also increase the coverage area, allowing for comprehensive surveillance of larger spaces or public areas. Moreover, deep learning models could be further fine-tuned and trained on more diverse datasets, accounting for various environmental conditions, lighting variations, and complex backgrounds, to reduce false positives and enhance detection accuracy. Another potential enhancement is the incorporation of facial recognition or behavior analysis to provide more context around the individual carrying the weapon, improving the system's ability to assess the threat level. Finally, the integration of cloud-based technologies could allow the system to handle larger volumes of data, provide faster processing speeds, and enable remote monitoring and management. These advancements would make firearm detection systems more robust and versatile, offering even more reliable security solutions in real-time situations.

APPENDIX

SAMPLE CODE

```
import cv2

import cvzone

import math

from ultralytics import YOLO

# Initialize the live camera feed (0 for default camera, or use 1, 2 for other connected cameras)

cap = cv2.VideoCapture(0)

# Load your YOLO model

model = YOLO("model.pt")

# Define class names

classnames = ['Firearm']

while True:

    ret, frame = cap.read()

    if not ret:

        print("Failed to capture video. Exiting...")

        break

    # Resize frame to a consistent size
```

```
frame = cv2.resize(frame, (640, 480))

# Run the YOLO model on the current frame

results = model(frame)

# Process detection results

firearm_detected = False

for info in results:

    parameters = info.boxes

    for box in parameters:

        x1, y1, x2, y2 = box.xyxy[0]

        x1, y1, x2, y2 = int(x1), int(y1), int(x2), int(y2)

        confidence = box.conf[0]

        conf = math.ceil(confidence * 100)

        class_detect = box.cls[0]

        class_detect = int(class_detect)

        class_detect = classnames[class_detect]

        if conf > 40:

            # Draw a rectangle and display the detected class

            cv2.rectangle(frame, (x1, y1), (x2, y2), (0, 255, 0), 2)

            cvzone.putTextRect(frame, f'{class_detect}', [x1 + 8, y1 - 12],
```

```
thickness=2, scale=1)
                firearm_detected = True
    # Display the frame
    cv2.imshow('Live Camera Feed', frame)
    # Terminate program if firearm detected
    if firearm_detected:
        print("Firearm detected! Terminating the camera feed...")
        break
    # Exit the loop when 'q' is pressed
    if cv2.waitKey(1) & 0xFF == ord('q'):
        print("Exiting...")
        break
# Release the camera and close all OpenCV windows
cap.release()
cv2.destroyAllWindows()
```

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Research Article

An Efficient Deep Learning-Based Firearm Detection System Using Yolov8

Dr. S.R. Menaka[1], Dr. R. Venkatesan[2], Dr. A. Sarankumar[3], K. Boomika[4], M. Devadharshini [5], J. Ramsurya[6]

[1] *Assistant Professor, Department of Information Technology, K.S.R. College of Engineering, Tiruchengode, TamilNadu, India. menaka@ksrce.ac.in*

[2] *Associate Professor, Department of Information Technology, Bannari Amman Institute of Technology Sathyamangalam, Erode, TamilNadu, India. venkat.ishva@gmail.com*

[3] *Assistant Professor, Department of Artificial Intelligence & Data Science, Coimbatore Institute of Technology Coimbatore, TamilNadu, India. saran.cit92@gmail.com*

[4] *Research Scholar, Department of Information Technology, K.S.R. College of Engineering, Tiruchengode, TamilNadu, India. ceitboomika25@gmail.com*

[5] *Research Scholar, Department of Information Technology, K.S.R. College of Engineering, Tiruchengode, TamilNadu, India. ceitdevadharshini25@gmail.com*

[6] *Research Scholar, Department of Information Technology, K.S.R. College of Engineering, Tiruchengode, TamilNadu, India. j.ramsurya007@gmail.com*

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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.

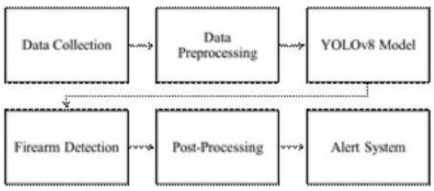

Fig. 1. Firearm Detection & Secured Alert System Workflow

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.

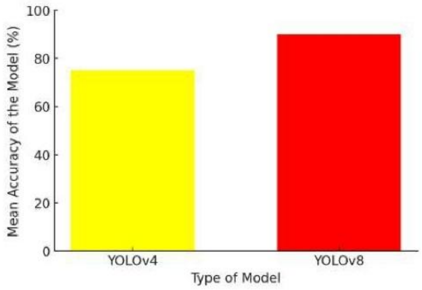

Fig. 2. Variation in Model Accuracy Across Cases

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.

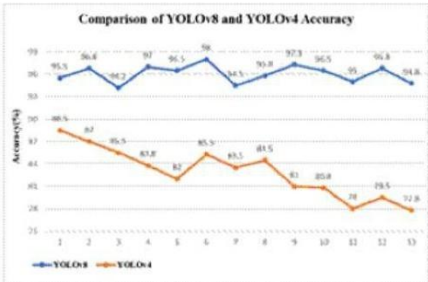

Fig. 3. Variation in Model Accuracy Across Cases

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.

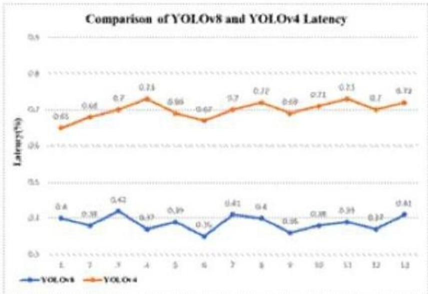

Fig. 4. Variation in Model Latency Across Cases

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.

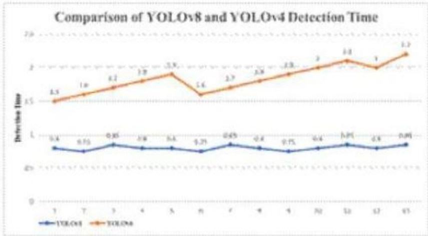

Fig. 5. Variation in Model Detection time Across Cases

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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