Weapon Detection Technologies for Surveillance under Different YoloV8 Models on Primary Data: Smart City Based Approach for Safe Society

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ABSTRACT

This comparison between the yolov8s.pt and yolov8x.pt YOLOv8 models is very important for real-time applications, particularly for object recognition and surveillance. Based on the results, the 95% precision and recall of the yolov8s.pt model, together with its 96% mean average precision, demonstrate the model's usefulness in situations requiring precise and quick object recognition. This model has potential applications in a variety of security systems, supporting security protocols in high-risk areas such as airports, public areas, and high-security enterprises by assisting in the quick identification of possible threats in real-time surveillance data.

Conversely, the yolov8x.pt model's better performance—which includes an astounding 98% precision and 99% mean average precision—highlights its effectiveness in demanding real-time applications that need exacting accuracy. Because of its complex capabilities, the model is a great fit for use in cutting-edge applications that require quick and accurate object recognition, such as autonomous driving technologies and sophisticated surveillance systems. By enabling quick detection and avoidance of possible risks or obstructions, its possible integration into autonomous cars might greatly improve road safety and advance the development of more dependable and safe autonomous driving systems.

Keywords: Convolutional Neural Network (CNN), down-sampling, Optimization, Weapons, detection, Surveillance, Object Detection, Thermal Imaging, Wave Scanning, Security Infrastructure.

Authors' Profile

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Ms. Yati Varshney is a student doing bachelors in technology in the field of Computer Science and Engineering from ABES Engineering College, Ghaziabad. She is a hardworking and curious student. Her hobbies are reading books, playing table tennis and exploring new things. She has a passion to learn and unlearn. She likes continuous learning**.**

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MOTIVATION

In an ever-evolving world, ensuring public safety and security has become a paramount concern. The use of surveillance systems to monitor public spaces, critical infrastructure, and various events has become a common practice. However, the growing challenges associated with security threats, including the presence of weapons, necessitate the development and deployment of advanced detection technologies.

This research aims to address these challenges by conducting a comprehensive study of weapon detection technologies in the context of video surveillance. The motivation behind this research is driven by the critical need to safeguard public spaces, minimize potential threats, and enable rapid response to security incidents. A thorough understanding of the state-of-the-art weapon detection techniques and technologies is pivotal in achieving these objectives.

The research will encompass a wide array of methodologies, from classical computer vision techniques to modern deep learning-based solutions. The overarching goal is to provide a detailed exploration of the strengths and weaknesses of various weapon detection technologies and to contribute to the advancement of surveillance systems. The findings of this study are expected to benefit security professionals, policymakers, and the general public by enhancing the effectiveness of surveillance systems and ultimately fostering a safer environment.

The significance of this study lies in its potential to inform the development of improved surveillance strategies, assist in the selection of appropriate technology for different contexts, and promote the responsible use of surveillance for the greater good of society. Through this comprehensive study, we aspire to contribute to the ongoing efforts to make public spaces more secure and peaceful.

SCOPE OF THE STUDY

This research encompasses a multifaceted exploration of weapon detection methodologies within video surveillance systems. In the field of object detection, the objective of this work is to provide a thorough comparative examination of the YOLOv5s (small version) and YOLOv5x (extra-large variant) models. Through the assessment of diverse performance measures and attributes, the research aims to offer discernments into the merits and demerits of every model variation, along with their suitability for actual object identification situations.

1 INTRODUCTION

In an age marked by evolving security challenges, the role of surveillance systems in ensuring public safety is pivotal. The ability to detect weapons in surveillance footage has become an urgent requirement for security and law enforcement. This research embarks on a comprehensive exploration of weapon detection methodologies, ranging from classical computer vision to modern deep learning techniques. It aims to assess the effectiveness, ethical considerations, and real-world applications of these technologies. By doing so, this research endeavors to contribute to the enhancement of public safety, ultimately fostering a more secure and peaceful environment in an ever-changing world.

1.1 Advancements in Weapon Detection Technologies and Systems

Triguero, F.H. et al (2023) and the team found that in recent years, there has been significant progress in the development of weapon detection technologies and systems. These advancements encompass a range of innovative solutions, including the use of advanced imaging techniques, such as millimeter-wave scanning and thermal imaging, to detect concealed weapons. In addition, the introduction of advanced millimeter wave scanners has improved security screenings by allowing high-resolution, non-invasive imaging for the detection of concealed weapons. Additionally, the use of acoustic gunshot detection systems has enhanced situational awareness by making it possible to locate gunfire occurrences quickly and precisely, which facilitates the taking of immediate action.

With more advanced and effective ways to recognize and reduce possible security concerns, these developments have completely changed the threat detection and prevention landscape **(Triguero F. H. et. Al, 2023) [12].**

Figure 1. The Resultant of the Weapon Detection shown by the Model

(Source:https://www.google.com/url?sa=i&url=https%3A%2F%2Fsci2s.ugr.es%2Fweapons-detection&psig=AOvVaw1GARtspSXB95hn_j538PPe&ust=1698559768979000&source=images&cd=vfe&opi=89978449&ved=0CBIQjRxqFwoTCKDfqq-KmIIDFQAAAAAdAAAAABAE)

Additionally, the integration of artificial intelligence and deep learning algorithms has improved the accuracy and efficiency of weapon detection systems, leading to more reliable and rapid identification of potential threats in various settings, including airports, public venues, and high-security facilities **(as per Figure 1)**.

1.2 Challenges and Solutions: Ensuring Effective Weapon Detection Measures

Narejo, S. et al (2021) proposed that despite the progress in weapon detection technology, various challenges persist in ensuring the effectiveness of these measures. Some of these challenges include the need to differentiate between real threats and false alarms, ensuring seamless integration of detection systems with existing security infrastructure, and addressing the limitations of current detection methods in identifying non-metallic or improvised weapons. Solutions to these challenges involve continuous research and development to enhance the capabilities of detection systems, as well as the implementation of comprehensive training programs for security personnel to effectively utilize these technologies and respond to potential threats **(Narejo, S. et. al., 2021) [7].**

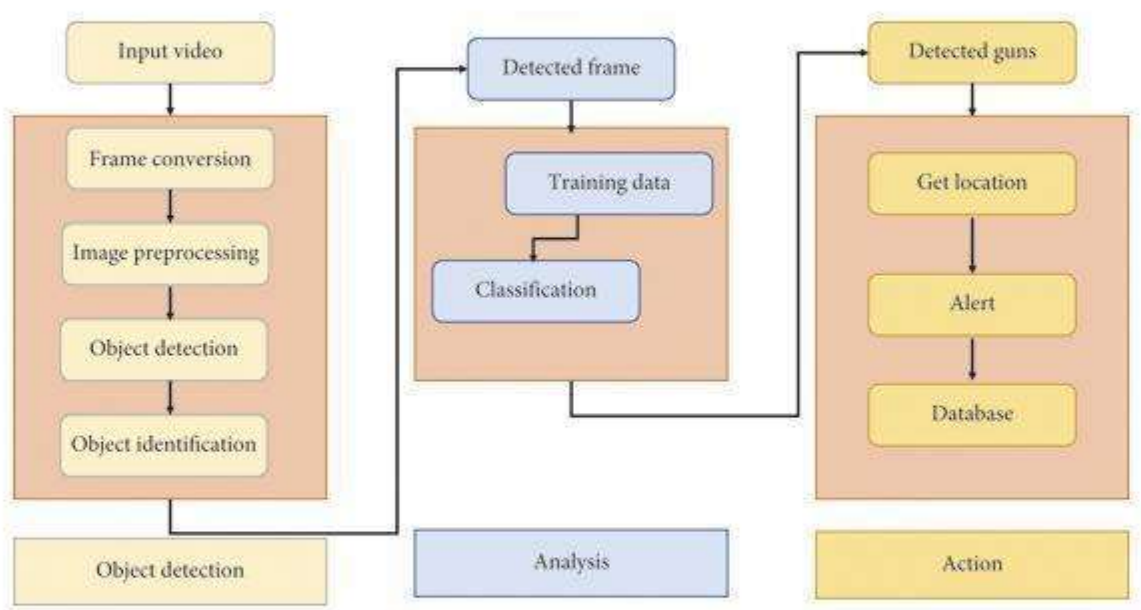


Figure 2. Flow Chart of the Solution which is used in Weapon Detection System

(Source:https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.hindawi.com%2Fjournals%2Fmpe%2F2021%2F9975700%2F&psig=AOvVaw3-VsFfBCwSu6bxRCDptOms&ust=1698559173129000&source=images&cd=vfe&opi=89978449&ved=0CBIQjRxqFwoTCOjHk5OImIIDFQAAAAAdAAAAABBy)

Solutions to these challenges involve continuous research and development to enhance the capabilities of detection systems, as well as the implementation of comprehensive training programs for security personnel to effectively utilize these technologies and respond to potential threats **(as per Figure 2)**.

1.3 The Influence of AI and Machine Learning on Weapon Detection Technology

Hnoohom, N, et.al. (2022) profound that the integration of AI and machine learning has revolutionized the field of weapon detection technology. By leveraging complex algorithms and pattern recognition techniques, AI-powered detection systems can analyze vast amounts of data and identify potential threats with greater accuracy and speed. Machine learning algorithms enable these systems to adapt and improve their performance over time, making them more adept at detecting concealed or disguised weapons **(Hnoohom N, et.al., 2022) [4].**

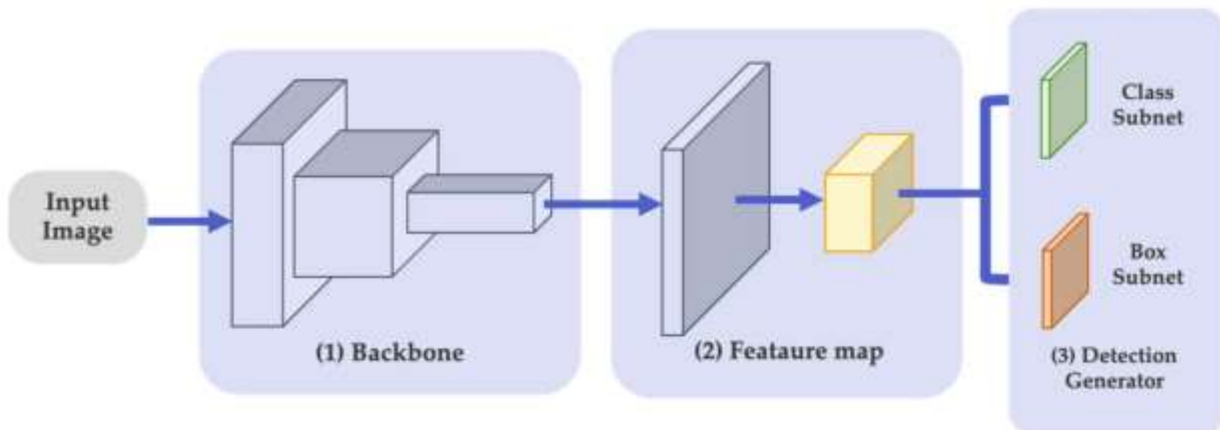


Figure 3. Architecture of an ACF (Armed CCTV Footage) system

Source:(https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.mdpi.com%2F1424-8220%2F22%2F19%2F7158&psig=AOvVaw0o7ZMlIZTH4UmG2l2freHr&ust=1698550913488000&source=images&cd=vfe&opi=89978449&ved=0CBIQjRxqFwoTCJCr97Dpl4IDFQAAAAAdAAAAABAJ)

Furthermore, the use of AI has facilitated the development of automated threat assessment systems, streamlining the decision-making process and enabling security personnel to respond swiftly to potential security breaches **(as per Figure 3)**.

1.4 Incorporating Weapon Detection Systems into Public Safety Infrastructures

Dave Fraser, et al (2022) researched that the integration of weapon detection systems into public safety infrastructures is crucial for enhancing security measures in various public spaces. This integration involves the strategic placement of detection devices in key locations, such as entrances, exits, and high-

traffic areas, to ensure comprehensive coverage and minimize blind spots **(Dave F., et.al. 2022) [2]**.

Figure 4. The Bounding Box with the Accuracy and Class Name Produced by the System

(Source:https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.securitysales.com%2Fnews%2Fweapons-detection-safe-active-shooters%2F&psig=AOvVaw0E6nOLU9HK6qfMObFQdFQ1&ust=1698551190869000&source=images&cd=vfe&opi=89978449&ved=0CBIQjRxqFwoTCMjWhbXql4IDFQAAAAAdAAAAABAt)

Additionally, effective integration requires close collaboration between security agencies, technology developers, and policymakers to develop standardized protocols for the deployment and operation of these systems. Moreover, public awareness campaigns and education initiatives are essential to inform the general public about the presence and importance of these detection systems in maintaining public safety and security **(as per Figure 4)**.

1.5 Ethical Implications and Privacy Concerns Surrounding Weapon Detection Technologies

NaikNithesh et.al (2022) researched that the widespread use of weapon detection technologies has raised significant ethical concerns and privacy issues. There is a growing need to balance the imperative of enhancing public safety with the protection of individual privacy rights. Ethical considerations revolve around ensuring the responsible and transparent use of weapon detection systems, minimizing the risk of discrimination or profiling, and safeguarding the dignity and rights of individuals during security screenings **(Naik N. et.al., 2022) [6].**

Figure 5. Privacy Concerns Surrounding Weapon Detection Technologies

(Source:https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.frontiersin.org%2Farticles%2F10.3389%2Ffsurg.2022.862322&psig=AOvVaw27g_5GcUoDNcSxIrkQnj8S&ust=1698558955527000&source=images&cd=vfe&opi=89978449&ved=0CBIQjRxqFwoTCNDKqauHmIIDFQAAAAAdAAAAABAE)

Furthermore, addressing privacy concerns requires the implementation of robust data protection measures, strict adherence to privacy regulations, and clear communication with the public regarding the purpose and scope of data collection through these systems. Understanding and addressing these ethical and privacy considerations are essential for fostering public trust and acceptance of weapon detection technologies **(as per Figure 5)**.

2 LITERATURE REVIEW

In a variety of settings, weapon detection systems are essential to maintaining public safety and security. An overview of the state of research and development in weapon detection is intended to be provided by this survey of the literature, with an emphasis on technological developments, difficulties, and ethical issues.

Olmos et.al, (2018) demonstrated that a unique automatic pistol detection system suitable for both control and surveillance applications is presented in this paper. Rephrasing this detection problem as the problem of minimizing false positives, we solve it as follows: i) using the output of a deep Convolutional Neural Network (CNN) classifier, we build the key training data-set; ii) we evaluate the best classification model under two approaches, namely the region proposal approach and the sliding window approach.

The Faster RCNN based model, which was trained on our new database, produced the most encouraging results. Even in low-quality YouTube videos, the greatest detector exhibits great potential and works well as an automated alarm system.

In 27 out of 30 situations, it successfully triggers the alarm following five consecutive true positives within a time interval of less than 0.2 seconds. In order to evaluate a detection model's effectiveness as an automatic detection system in videos, we additionally establish a new metric called Alarm Activation Time per Interval (AATpI) **(Olmos et.al, 2018) [9].**

Castillo et.al., (2019) exhibited that automated identification of cold steel weapons in the hands of one or more people in surveillance footage can aid in the decrease of crime. However, there is a significant issue with the recognition of these metallic objects in videos: their surface reflection at medium to high illumination levels distorts their outlines in the image, making their detection difficult.

This piece has two goals in mind:

- **(i)** Convolutional Neural Networks (CNN) will be used to build an automatic cold steel weapon detection model for video surveillance.
- **(ii)** DaCoLT (Darkening and Contrast at Learning and Test stages) will be suggested as a brightness-guided preprocessing method to increase the model's robustness to light conditions.

Excellent results are obtained when using the developed detection model as an automatic alarm system in video surveillance and as a detector for cold steel weapons **(Castillo et. al, 2019) [1].**

Olmos et.al, (2019) propounded that in recent years, there have been notable advancements in object detection models. Cutting edge detectors are end-to-end CNN based models that achieve good mean average precisions, approximately 73%, on high quality image benchmarks. Still, a lot of false positives are generated by these models in low-quality videos, including surveillance footage. In order to direct the detection model's attention to the region of interest where the action is most likely to occur in the scene, this research suggests a novel image fusion technique.

Our suggestion is to construct an affordable, symmetric dual camera system that can calculate the disparity map and utilize this data to enhance the process of choosing potential regions from the input frames.

Based on our findings, the suggested method is suitable for object detection in surveillance footage since it lowers the quantity of false positives while simultaneously enhancing the detection model's overall performance **(Olmos et.al., 2019) [10].**

Pérez-Hernández et al (2020) demonstrated that in many fields, particularly video surveillance, the ability to discriminate between small objects when handled by hand is crucial. Currently, it is difficult to identify these objects in photos using Convolutional Neural Networks (CNNs). In this paper, we propose to use binarization techniques to improve the robustness, accuracy, and reliability of small object detection handled similarly. We suggest utilizing Object Detection with Binary Classifiers, a two-level deep learning-based methodology, to enhance their detection in videos. The input frame's candidate regions are chosen at the first level, and a CNN-classifier-based binarization technique with One-Versus-All or One-Versus-One is then applied at the second level.

Specifically, we address the video surveillance task of identifying weapons and items that, when handled with the hand, could be mistaken for a knife or a handgun. Taking into account six items, we build a database: a handgun, a knife, a smartphone, a bill, a purse, and a card. According to the experimental study, compared to the baseline multi-class detection model, the suggested methodology results in fewer false positive **(Pérez-Hernández et. al, 2020) [11].**

Lamas et.al., (2022) propounded that when it comes to weapon detection in video surveillance, using CNN-based object detection models still results in a lot of false negatives. Within this framework, the majority of previous studies concentrate on a single class of weaponry, primarily firearms, and enhance the identification using various pre- and post-processing techniques. Utilizing human stance data to enhance weapon identification is an intriguing strategy that hasn't been thoroughly investigated yet. This research provides a top-down methodology that uses a weapon identification model to assess the hand regions once they are first identified using the human pose estimation as guidance. We proposed a new component, termed Adaptive pose factor that considers the body's distance from the camera for an ideal localization of each hand region.

In both indoor and outdoor video-surveillance scenarios, our tests demonstrate the superior robustness of the top-down Weapon Detection over Pose Estimation (WeDePE) methodology over the alternative bottom-up approach and state-of-the-art detection algorithm **(Lamas et.al., 2022) [5].**

Narejo, S. et al. (2021) propounded that every year, a significant portion of the world's population deals with the effects of gun violence. This study presents an automated computer-based system designed to recognize common weaponry, with a particular emphasis on rifles and pistols. The domains of object identification and recognition have made significant strides recently thanks to developments in deep learning and transfer learning. The "You Only Look Once" (YOLO V3) object detection model, which was trained on our own dataset, is used in our investigation. The training results validate that YOLO V3 performs better than both YOLO V2 and traditional convolutional neural networks (CNNs). Notably, since we used transfer learning for model training, our methodology does not necessitate large GPUs or significant computational resources. By incorporating this model into our surveillance system, we want to lessen the number of fatalities and possibly even the number of manslaughter and mass murders. Furthermore, our suggested approach has the potential to be implemented in cutting-edge security and surveillance robots to identify weapons or dangerous objects, averting any possible threats to human life **(Narejo, S. et. al., 2021) [7].**

Dugyala, R. et.al. (2023) exhibited that a potential violent scenario's early warning mechanism is provided by weapon detection (WD). The detection of firearms is still a difficult task even with the combination of advanced closed-circuit television (CCTV) technology and deep learning (DL) algorithms. This work presents a new WD model that uses the PELSF-DCNN methodology. First, preprocessing and frame conversion are applied to the supplied video. Then, we use the YOLOv8 method to find objects in these preprocessed frames. In parallel, motion estimation is carried out on the preprocessed images by applying the DS method to guarantee thorough coverage of all pertinent data. The weapons that have been identified then go through a sliding window method that includes the motion-estimated frames.

The silhouette score is calculated for both items and detected people. Following feature extraction, the CSBO algorithm is used to choose the most important features. The YOLOv8 output and these particular features are fed into the PELSF-DCNN classifier. In order to ascertain the quantity of firearms in each frame, a confidence score is finally calculated. The suggested strategy outperforms current techniques in terms of efficiency, according to experimental evaluation **(Dugyala, R. et.al. 2023) [3].**

O. Rasheed et.al. (2022) showcased that with more and more bank and retail robberies occurring on a regular basis, protecting people's safety and security has become a major concern in the modern era. This highlights how vital it is to have a strong security system that can both maintain peace and safety and significantly reduce the possibility of such incidents. Despite being widely used, traditional CCTV surveillance systems are comparatively ineffective due to their reliance on human interaction. Through the integration of Artificial Intelligence (AI) with Object Detection, the system may greatly improve the speed and efficiency of threat identification. This project uses a dataset of 7801 photos to train the state-of-the-art YOLO (You Only Look Once) object identification technology, which is used to identify handguns and rifles.

The 'MULTIPLATFORM' system is based on a Raspberry Pi or Jetson Nano and has a Graphical User Interface (GUI) that can be accessed via an HTML-CSS online portal and a mobile Android application developed with Android Studio. When a weapon is detected, the system takes a screenshot and alerts the user/manager via NODEMCU (ESP8266) and the user's web site. The manager is given the choice to select the red button to recognize the threat or the green button to ignore the alert. If the danger level is confirmed, the system immediately alerts the appropriate authorities—such as surrounding police stations—via a message or call made possible by the GSM module.

The system immediately notifies the relevant authorities if the manager does not respond within 15 seconds. The system's effectiveness was demonstrated by the execution of a simulated robbery scenario, wherein the weapon was successfully detected **(O. Rasheed et.al.2022) [8].**

The tabular summary of research papers have been given below **(as per Table 1).**

Table 1. Tabular Summary for literature Review Based Papers

Title and Authors	Summary	Methodology, Dataset, and Algorithm Used	Conclusion

Automatic Handgun Detection in Videos Using Deep Learning **(Olmos et.al, 2018) [9]**.	Presents a unique automatic pistol detection system that minimizes false positives, utilizing a Faster RCNN model trained on a new database.	Methodology: Faster RCNN, Dataset: New database, Algorithm: Deep CNN	Concludes that the proposed system effectively triggers alarms based on multiple true positives, with the potential for use as an automated alarm system.
Brightness Guided Preprocessing for Automatic Cold Steel Weapon Detection **(Castillo et.al, 2019) [1]**.	Proposes a CNN-based approach for automatic cold steel weapon detection, emphasizing the DaCoLT preprocessing method to enhance model robustness to light conditions.	Methodology: CNN, Dataset: Not specified, Algorithm: DaCoLT	Demonstrates the effectiveness of the suggested methodology for detecting cold steel weapons in surveillance videos, highlighting its potential for use as an automatic alarm system.
A Binocular Image Fusion Approach for Minimizing False Positives in Handgun Detection with Deep Learning **(Olmos et.al, 2019) [10].**	Suggests an image fusion technique to reduce false positives in handgun detection, employing a novel approach with a dual camera system and disparity map calculations.	Methodology: Image fusion, Dataset: Not specified, Algorithm: Dual camera system	Concludes that the proposed method effectively reduces false positives and enhances the overall performance of the detection model in surveillance footage.

Object Detection Binary Classifiers Methodology Based on Deep Learning to Identify Small Objects **(Pérez-Hernández et. al, 2020) [11].**	Proposes a methodology using binary classifiers for small object detection in videos, focusing on weapon identification and employing binarization techniques.	Methodology: Binary classifiers, Dataset: Small object database, Algorithm: Object Detection with Binary Classifiers	Indicates that the suggested methodology results in fewer false positives compared to the baseline multi-class detection model, enhancing small object detection in surveillance scenarios.
Human Pose Estimation for Mitigating False Negatives in Weapon Detection **(Lamas et.al, 2022) [5]**.	Introduces a top-down methodology for weapon detection in video surveillance, incorporating human pose estimation to enhance detection robustness.	Methodology: Human pose estimation, Dataset: Not specified, Algorithm: Adaptive pose factor	Demonstrates the superior robustness of the proposed top-down Weapon Detection over Pose Estimation (WeDePE) methodology in both indoor and outdoor video-surveillance scenarios.

Weapon Detection Using YOLO V3 for Smart Surveillance System **(Narejo, S. et. al. 2021) [7].**	Presents an automated system utilizing YOLO V3 for recognizing firearms, emphasizing the reduction of false positives and the potential for application in surveillance and security robots.	Methodology: YOLO V3, Dataset: 7801 images, Algorithm: YOLO V3	Emphasizes the capability of the proposed system to mitigate fatalities and reduce the occurrence of manslaughter and mass killings, highlighting its potential for integration into security and surveillance robotics.
Weapon Detection in Surveillance Videos Using YOLOV8 and PELSF-DCNN **(Dugyala, R. et.al. 2023) [3]**	Introduces a WD model using the PELSF-DCNN methodology for video surveillance, emphasizing silhouette score calculation and confidence score computation for firearm detection.	Methodology: PELSF-DCNN, Dataset: Not specified, Algorithm: YOLOV8	Indicates the superior efficiency of the suggested strategy compared to existing techniques, highlighting its potential for application in automated surveillance systems.

Multiplatform Surveillance System for Weapon Detection using YOLOv5**(O. Rasheed et.al, 2022) [8].**	Discusses the development of a multiplatform surveillance system using YOLOv5 for weapon detection, with the capability to send alerts and notifications to authorities in case of potential threats.	Methodology: YOLOv5, Dataset: 7801 photos, Algorithm: YOLOv5	Demonstrates the effectiveness of the developed system in detecting weapons and its potential for real-time threat prevention and notification to authorities in case of security breaches.

3 METHODOLOGY and SETUP DESIGN of EXPERIMENT

3.1 Algorithms Used

The You Only Look Once (YOLO) technique, which makes it possible to identify objects in photos and videos in real time, is a significant advancement in object detection. YOLO employs a single neural network to predict bounding boxes and class probabilities directly from entire images in a single assessment, in contrast to conventional region-based convolutional neural networks (R-CNNs), which entail several phases and intricate computations. This method greatly expedites the detecting process without sacrificing precision **(Nandini, A. et al., 2024) [16]**.

3.2 Network Requirements

Convolution Neural network (CNN) is one of the most effective methods for sentiment analysis. This research uses CNN network. CNN has a convolution layer to extract the large piece of text in units which is beneficial for this research. This research can be executed by both the client and the server.

3.3 Datasets

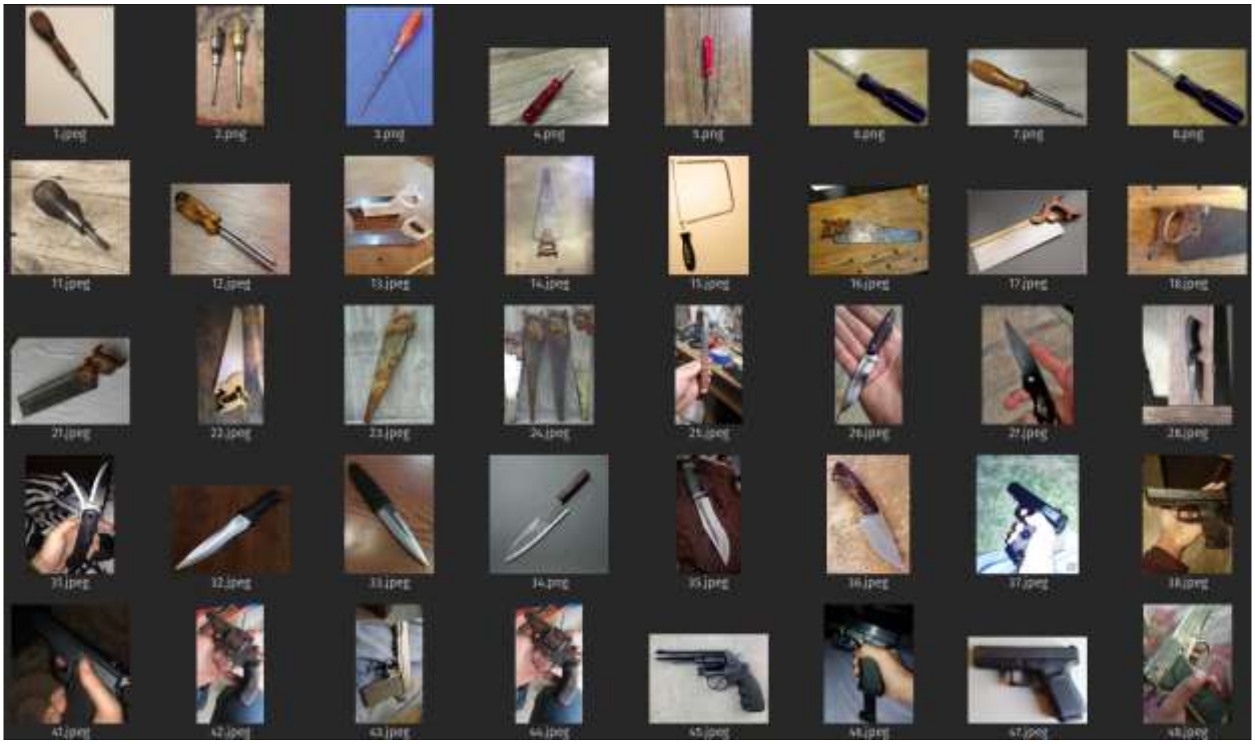


Figure 6. Primary images of four classes

The dataset used for this research consists of 4 different harmful weapons: knife, guns, screwdriver and handsaw. There are equal ratios of the images of each weapon **(as per Figure 6)**.

3.4 Hardware Requirements

● Ram- 8GB (minimum)

● Processor- i3 (minimum)

3.5 Software Requirements

1) Libraries- MLP, Sklearn, seaborn, matplotlib, NumPy, pandas,

2) Ultralytics library **(Prabhakaran, G. et al., 2024) [17].**

3.6 OS Requirements

It can work even with windows, Linux, mac-os. Because this research only needs ideas for running the code with the local software where the webcam can access.

3.7 Steps of Executions

The steps for executing weapon detection using a webcam typically involve the following:

- Setup Environment
- Collect and Prepare Data
- Train the Model
- Webcam Setup
- Capture Webcam Stream
- Preprocessing
- Weapon Detection
- Post-processing
- Display Results
- Real-Time Processing
- Testing and Validation

METHODOLOGY

3.8 Flow Chart

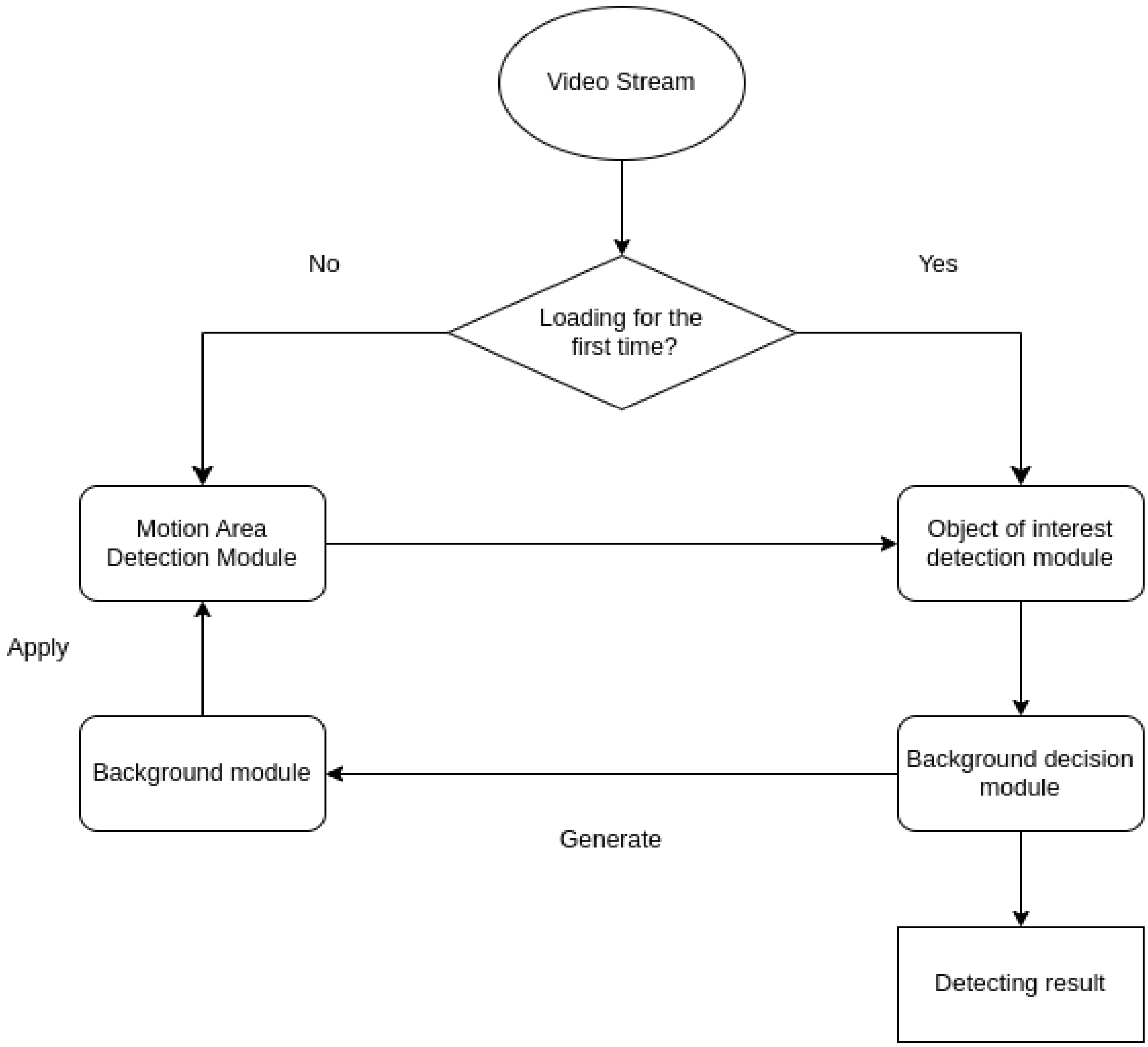


Figure 7. Flowchart for Weapon Detection System

It starts by capturing and collecting the input, which might be an image or a video stream. After that, the input is preprocessed in order to get it ready for the model. The next step is to load a pre-trained object identification model and run a loop over each frame of the input. The object identification model is applied to the frames during the loop, and post-processing operations like filtering and non-maximum suppression are used to polish the outcomes. The processed frames are either shown in real-time (for video streams) or stored (for photos), depending on the kind of frame processing used. Bounding boxes and labels are created on the frames to indicate the discovered items. Once all frames have been analyzed, the social guard procedure is finished **(as per Figure 7)**.

3.9 Block Diagram

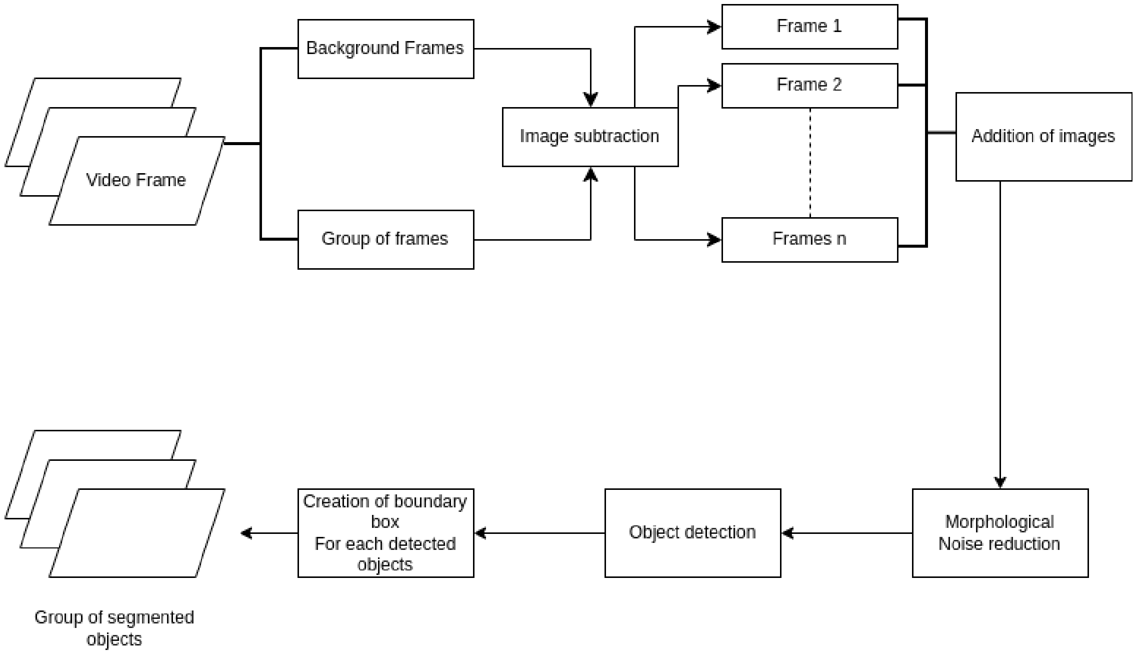


Figure 8. Block diagram of the Social Guard which performs the Real Time Detection

It involves various important parts. The system receives real-time data from the input source, which might be a camera or video stream. To get the data ready for the YOLOv8 model, preparatory operations including scaling and normalization are performed. The deep learning model YOLOv8 then conducts object recognition and creates bounding boxes with appropriate confidence scores around discovered items. The detections are refined using post-processing, which eliminates duplicates and false positives using non-maximum suppression **(as per Figure 8) (Vivekrabinson, K. et al., 2024)[18]**.

The locations, class labels, and confidence scores of the identified objects are included in the final output, which may be utilized for additional real-time decision-making in robotics, autonomous navigation, or surveillance applications. YOLOv8 makes use of optimizations such as model architectural improvements and hardware acceleration to reach real-time performance, guaranteeing effective processing of the continuous input stream.

3.10 Use Case Diagram

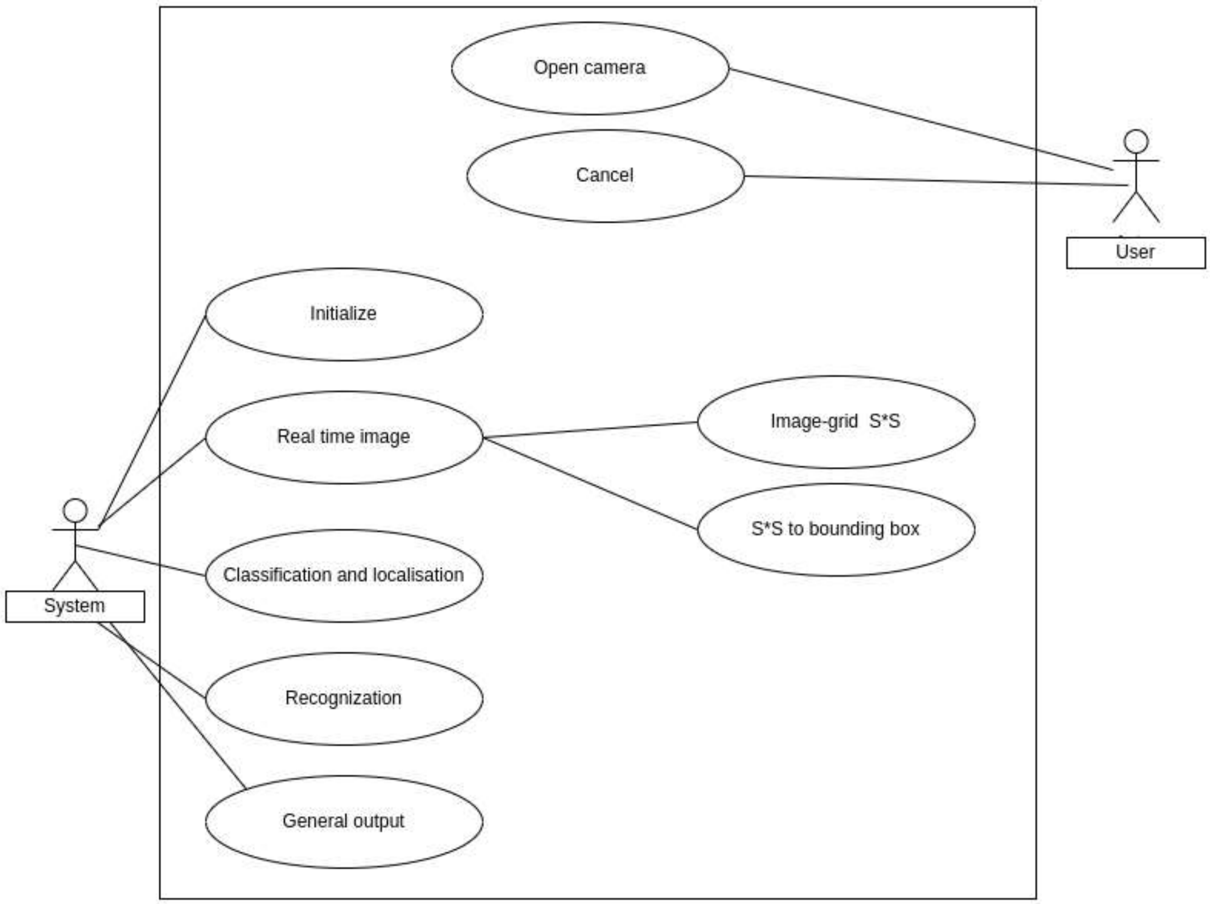


Figure 9. Use Case Diagram of the Social Guard which performs the Real Time Detection

There are two key characters in the use case diagram for real-time object identification using YOLOv8: the "User" and the "Object Detection System." The system gathers and analyzes real-time input data at the user's request. After preprocessing the data, YOLOv8 detects objects, producing bounding box predictions and confidence ratings. The detections are improved using post-processing approaches including non-maximum suppression. For the user's visual feedback, the complete output, which includes item placements, labels, and scores, is shown in real-time. In some applications, like robots or autonomous cars, the system can optionally start real-time activities or reactions depending on the information about the observed objects **(as per Figure 9)**.

4 RESULT AND DISCUSSIONS

This research is a comparison between two models of YOLOv8 which are yolov8s.pt and yolov8x.pt. Because of its quick and precise design, YOLOv8 can be used for a variety of real-time object identification surveillance, and autonomous cars, among other applications. It can recognize many things in a single pass by using deep convolutional neural networks to detect objects within pictures or video frames. Here, performance matters because security is a major topic for today's life.

4.1 Performance of Yolov8s.pt model

The pre-trained YOLOv8s model checkpoint file is referred to in the yolov8s.pt file. One of the variations on the YOLOv8 model is called YOLOv8s, and the 's' stands for tiny version. This analysis of performance is based on metrics and training. These graphs show the vertical axis for performance metric and horizontal axis for epochs. The metrics calculate the mean average precision (mAP), precision and recall of this model.

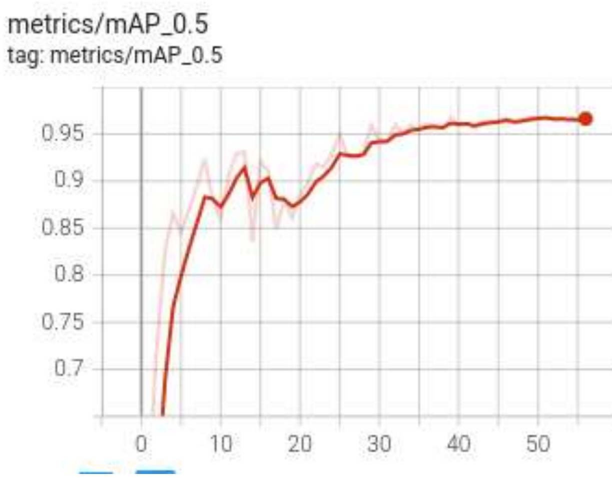


Figure 10. Mean Average Precision Graph of Yolov8s.pt Model

In this figure the threshold value is 0.5 and this threshold is the Intersection over union. The graph shows better object identification performance by a higher mAP at 0.5 IoU value, which suggests that the model can correctly identify items at the designated IoU threshold with a respectable degree of precision and recall. Here the accuracy value is 0.96 which means 96% **(as per Figure 10)**.

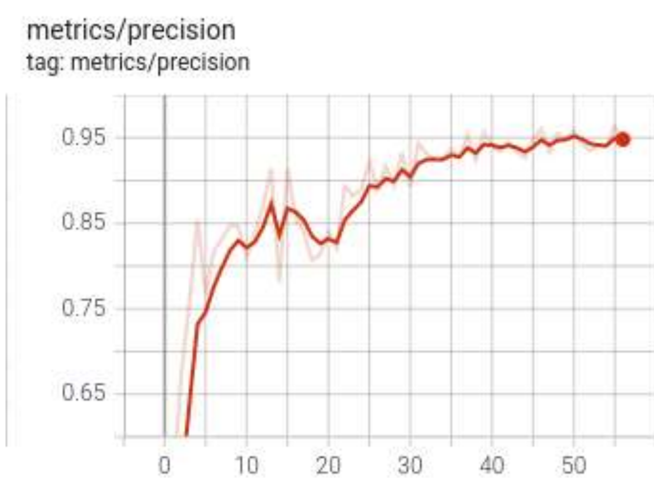
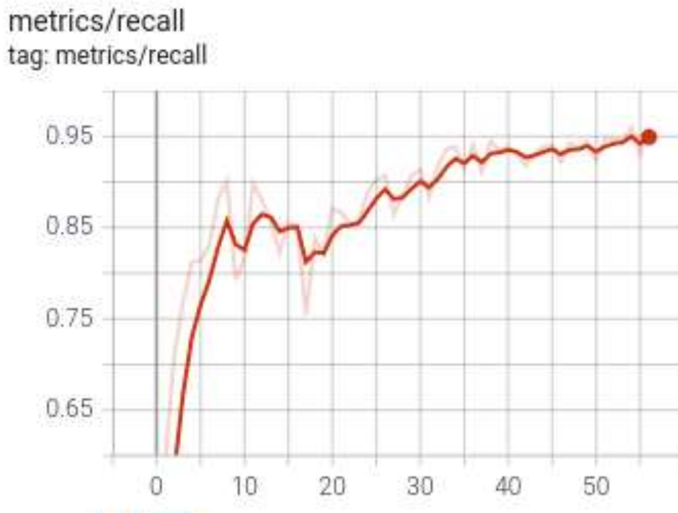


Figure 11. Precision Graph of Yolov8s.pt Model

In this figure the model shows the ability to minimize false positives i.e. precision. There it is clearly shown that the precision percentage value goes to 0.95 that means the precision is 95% which is good for



the model **(as per Figure 11)**.

Figure 12. Recall Graph of yolov8s.pt Model

In this figure the recall curve is shown which defines how successfully the capturing a significant proportion of the true positive instances within the dataset. The graph shows the accuracy score of 95%. The high recall score suggests that the model effectively captures a substantial number of relevant instances in the dataset **(as per Figure 12)**.

Figure 13. Training Box Loss Graph of Yolov8s.pt Model

In this figure the graph shows the box loss .This parameter is only used in YOLO models. This is used for measuring the performance of the model. The vertical axis shows the percentage and the horizontal axis shows the epochs. This graph shows the decrease in the loss with the increasing number of the epochs. This loss can be acceptable because it is low for this model **(as per Figure 13)**.

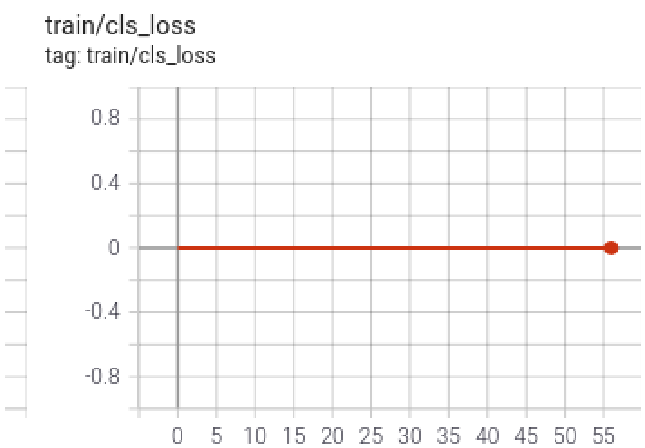


Figure 14. Training Classification Graph of Yolov8s.pt Model

In this figure the graph shows the classification loss. This parameter is only used in YOLO models. The capacity of the model to accurately classify detected items into various predetermined groups or classes is the main topic of this study. This zero value shows how perfectly classification is done by the model during the training process for the current batch or epoch **(as per Figure 14)**.

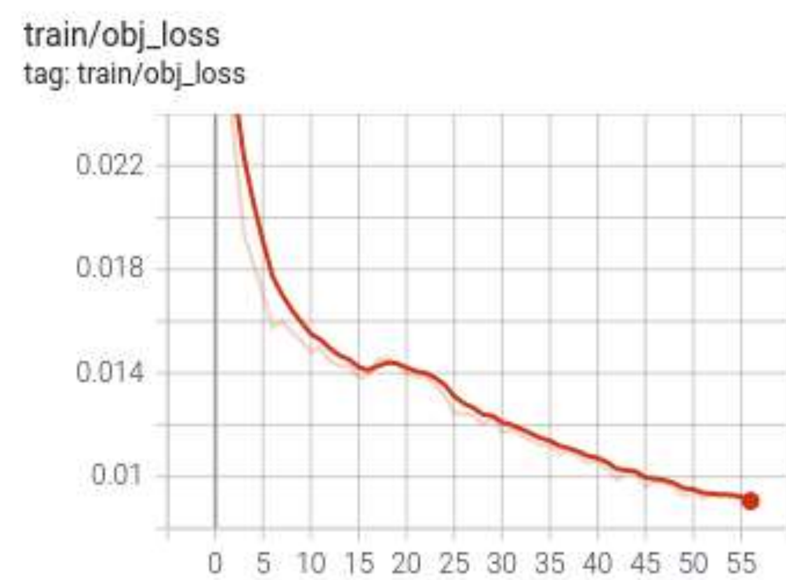
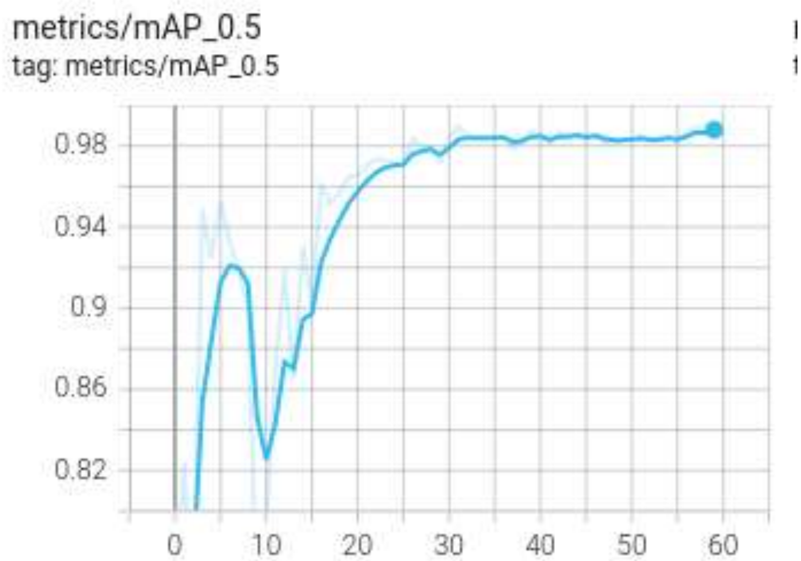


Figure 15. Training Object Loss Graph of Yolov8s.pt Model

In this figure the graph shows the object loss .This parameter is only used in YOLO models. This is used to identify how perfectly the object is detected within the bounding box. According to this graph it is shown there is no loss to identify the object which means the overall performance of the model is high and fast **(as per Figure 15)**.

4.2 Performance of Yolov8x.pt

The pre-trained YOLOv8x model checkpoint file is referred to in the yolov8x.pt file. One of the variations on the YOLOv8 model is called YOLOv8x, and the 'x' stands for extra-large version. This analysis of performance is based on metrics and training. These graphs show the vertical axis for performance metric and horizontal axis for epochs. For this model the epochs are more than the yolov8s



model. The metrics calculate the mean average precision (mAP), precision and recall of this model.

Figure 16. Mean Average Precision Graph of Yolov8x.pt Model

In this figure the threshold value is 0.5 and this threshold is the Intersection over union. The graph shows better object identification performance by a higher mAP at 0.5 IoU value, which suggests that the model can correctly identify items at the designated IoU threshold with a respectable degree of precision and recall. This graph shows the mean average precision is 0.99 something which means 99% of accuracy which is good accuracy for the model **(as per Figure 16)**.

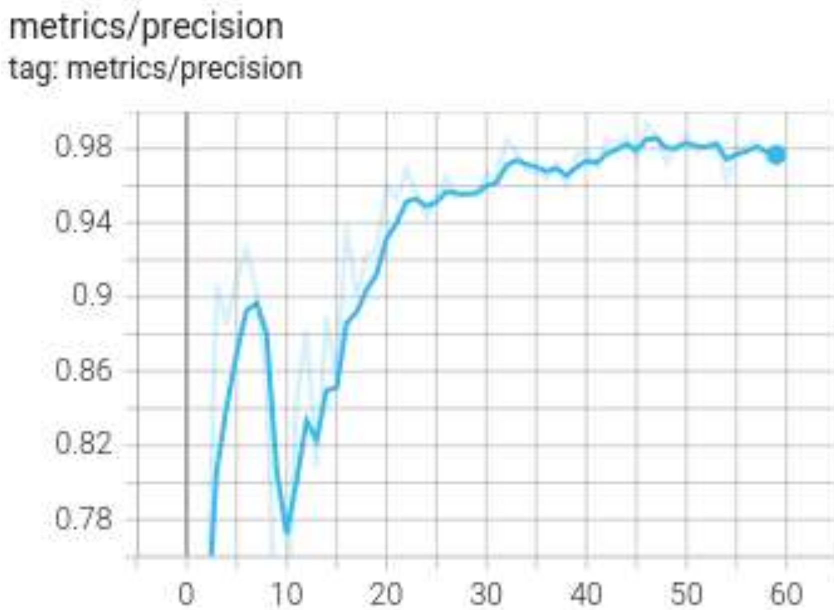


Figure 17. Precision Graph of Yolov8x.pt Model

In this Figure the model shows the ability to minimize false positives i.e. precision. There it is clearly shown that the precision percentage value goes to 0.98 that means the precision is 98% which is good for the model **(as per Figure 17)**.

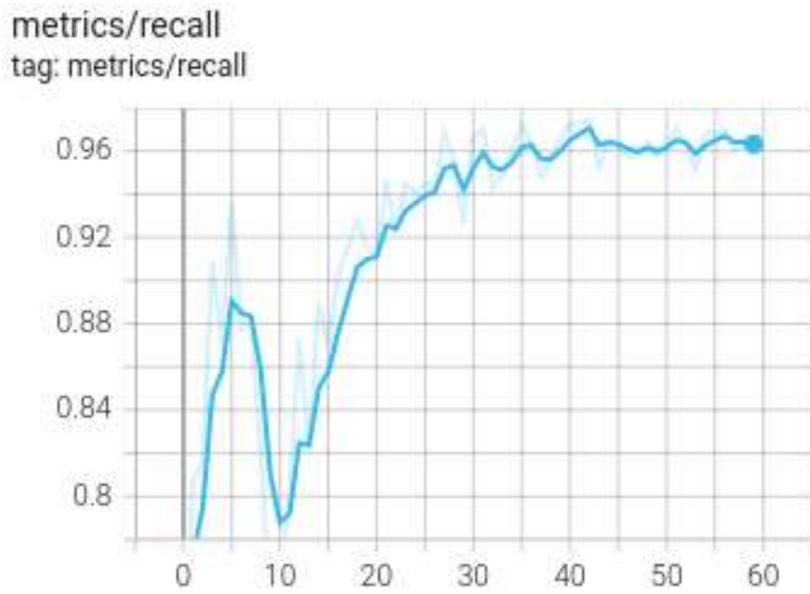


Figure 18. Recall Graph of Yolov8x.pt Model

In this figure the recall curve is shown which defines how successfully the capturing a significant proportion of the true positive instances within the dataset. The graph shows the recall score of 96% .The high recall score suggests that the model effectively captures a substantial number of relevant instances in the dataset. But this is more accurate and fast than the yolov8s model **(as per Figure 18)**.

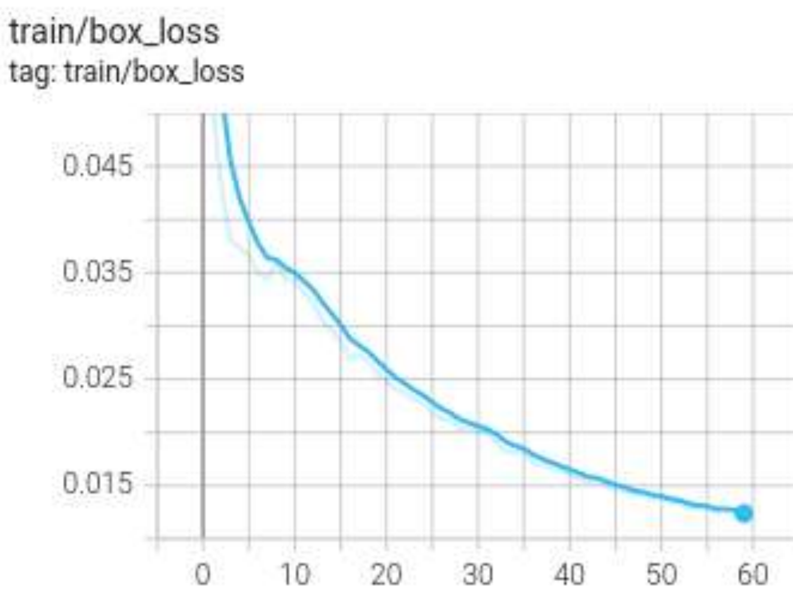


Figure 19. Training Box Loss Graph of Yolov8x.pt Model

In this figure the graph shows the box loss. This parameter is only used in YOLO Models. This is used for measuring the performance of the model. The vertical axis shows the percentage and the horizontal axis shows the epochs. This graph shows the decrease in the loss with the increasing number of the epochs. This loss can be acceptable because it is low for this model but this gives less loss as compared to Yolov8s.pt model**(as per Figure 19)**.

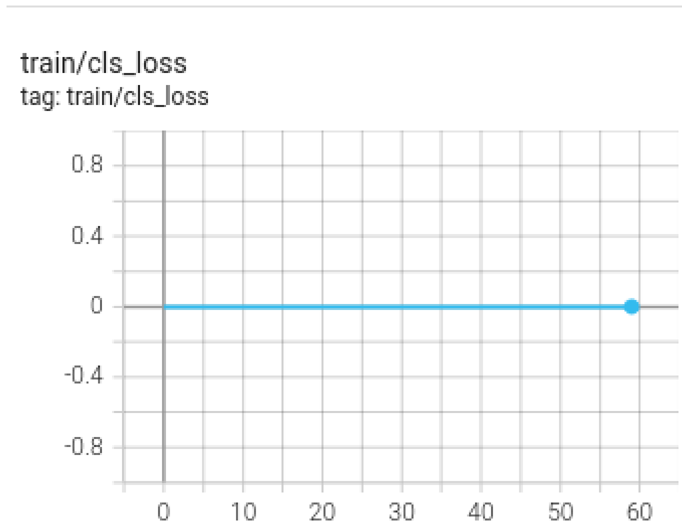


Figure 20. Training Classification Loss Graph of Yolov8x.pt Model

In this figure the graph shows the classification loss .This parameter is only used in YOLO models. The capacity of the model to accurately classify detected items into various predetermined groups or classes is the main topic of this study. This zero value shows how perfectly classification is done by the model during the training process for the current batch or epoch. It means both models are the best fitted for classification loss **(as per Figure 20)**.

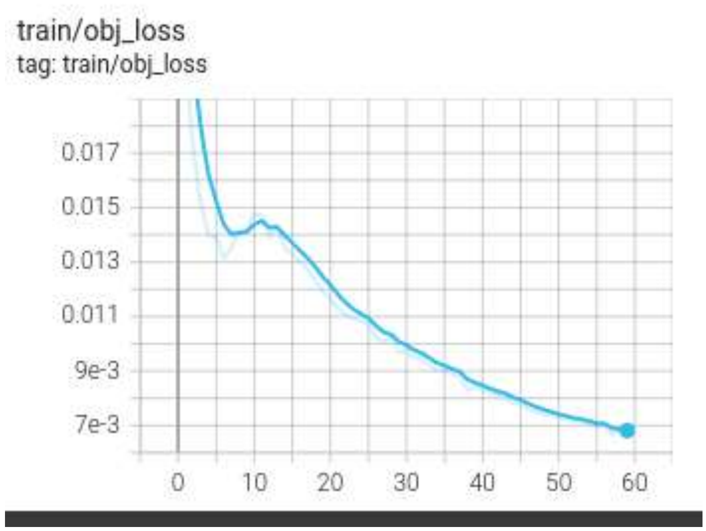


Figure 21. Training object Loss Graph of Yolov8x.pt Model

In this figure the graph shows the object loss .This parameter is only used in YOLO models. This is used to identify how perfectly the object is detected within the bounding box. According to this graph it is shown there is no loss to identify the object which means the overall performance of the model is high and fast. This loss can be acceptable because it is low for this model but this gives less loss as compared to yolov8s.pt Model**(as per Figure 21)**.

4.3 Discussions

Table 2. Tabular Summary for Measuring Models Performance

Model	mAP at 0.5 IoU	Precision	Recall	Box Loss	Classification Loss	Object Loss
YOLOv8s.pt	0.96 (96%)	0.95 (95%)	0.95 (95%)	Acceptable, Low	0	No Loss
YOLOv8x.pt	0.99 (99%)	0.98 (98%)	0.96 (96%)	Acceptable, Low (Less than YOLOv8s)	0	No Loss (Less than YOLOv8s)

In conclusion, while both models demonstrated strong capabilities in object detection, the yolov8x.pt model exhibited superior performance metrics, highlighting its enhanced accuracy, precision, and efficiency compared to the yolov8s.pt model **(as per Table 2) (Nayudu, P.P. et al., 2023) [13]**.

Table 3. Tabular Summary for Measuring Our Models with Other State of Arts

Model	Key features	Limitations	Accuracy
YOLOv3[7]	Efficient detection with the proposed methodology, outperforming existing techniques.	Limited discussion on potential challenges in silhouette score calculation accuracy under varying environmental conditions.	98.89

YOLOv5, YOLOv4, YOLOv3[8]	Enhanced threat mitigation capabilities, integration with multiple platforms, and successful demonstration in simulated robbery scenarios.	Limited discussion on potential challenges in integrating the multiplatform system into diverse surveillance environments.	87%,84%,77 % respectively
ODeBiC[11]	Improved robustness over the bottom-up approach and state-of-the-art detection algorithms.	Challenges related to potential variations in human stance data are not explicitly discussed.	57%
Presented Model: YOLOv8s	1. Strong performance in detecting objects accurately. 2. Efficient localization of objects. 3. Robust object classification and minimal loss during training.	Relatively lower overall performance compared to YOLOv8x, with slightly lower mAP, precision, and recall.	96%
Presented Model: YOLOv8x	1. Exceptional object detection accuracy 2. Superior precision and comprehensive detection capabilities.	The model might demand more computational resources compared to YOLOv8s due to its superior performance. Require more complex hardware and infrastructure, making it less accessible for applications with limited resources compared to YOLOv8s.	99%

In conclusion, the yolov8x.pt model achieved an outstanding mAP (mean average precision) at 0.5 IoU (Intersection over Union) of 99%, indicating its exceptional ability to accurately detect objects even in challenging scenarios. While the yolov8s.pt model also exhibited strong performance, its metrics were slightly lower compared to the yolov8x.pt model. It achieved a respectable mAP at 0.5 IoU of 96% and precision and recall values of 95%. This concludes that both models demonstrated strong capabilities in object detection, the yolov8x.pt model exhibited superior performance metrics, highlighting its enhanced accuracy, precision, and efficiency compared to the yolov8s.pt model **(Singh, R. et al., 2023)[14]; (Challoob, A.L. et al., 2024)[15].**

5 NOVELTIES

- This research uses the newest technology that is YOLOv8, this version was developed in 2022 and there is only a little research on it.

- This research is based on the solution which is done by the researchers (Social Guard). This same solution is used in this solution for the comprehensive study.
- This study deprived the metrics parameters and training parameters used by the YOLO for evaluation of the model's accuracy.
- This study mainly focused on the differentiating features of the yolov8s.pt and yolov8x.pt models.

6 RECOMMENDATIONS

This research presents a pioneering approach utilizing the cutting-edge YOLOv8 technology, a recently developed version with limited prior research, emphasizing its novelty and significance in the field. Leveraging the solution pioneered by the researchers at Social Guard, the study offers a comprehensive exploration of this approach's applicability and efficacy. Additionally, the study delves into the essential metrics and training parameters employed by the YOLO framework to assess the model's accuracy, thereby providing a thorough understanding of the evaluation process. Focusing on the distinguishing characteristics between the yolov8s.pt and yolov8x.pt models, the research sheds light on the nuanced capabilities and potential implications of these distinct iterations, contributing to a deeper comprehension of their practical implications and relevance within the realm of weapon detection and surveillance systems.

7 FUTURE RESEARCH DIRECTIONS AND LIMITATIONS

7.1 Limitations

1. Accurately identifying small or far-off weaponry may be difficult for YOLO, particularly in low-resolution or poorly visible photos or videos.
2. Scenes with a lot of clutter or locations with complicated backdrops may make YOLO perform worse.
3. Variations in illumination, including glare, shadows, or dimly lit areas, could affect how well the program recognizes firearms.

7.2 Future Directions

1. Explore advanced data augmentation techniques to enhance the diversity and quality of the training dataset
2. Examine the creation of upgraded YOLO architectures, as they might provide better real-time processing capabilities, increased accuracy, and higher performance.
3. Examine implementing adaptive learning techniques so that the system can keep learning and adjusting to new threats and weapon patterns.

8 CONCLUSIONS

In this research, a comprehensive comparison between two models of YOLOv8, namely yolov8s.pt and yolov8x.pt, was conducted. YOLOv8, known for its rapid and accurate object identification capabilities, is applicable in various real-time surveillance scenarios and autonomous driving applications, emphasizing the crucial role of performance in addressing contemporary security concerns.

For the yolov8s.pt model, the analysis indicated a mean average precision (mAP) of 96%, with both precision and recall scores at 95%, showcasing the model's proficient object identification capabilities. Additionally, the model demonstrated acceptable box, classification, and object losses, highlighting its overall high performance and efficiency.

On the other hand, the yolov8x.pt model showcased even higher performance metrics, with anmAP of 99% and precision of 98%, indicating superior accuracy and precision compared to the yolov8s.pt model. The recall score was slightly lower at 96%, signifying the model's effective capturing of relevant instances. Notably, the model exhibited minimal box, classification, and object losses, further emphasizing its exceptional performance and speed compared to the yolov8s.pt model.

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ADDITIONAL READINGS

- **Weapon Detection Using Faster R-CNN Inception-V2 for a CCTV Surveillance System** (https://ieeexplore.ieee.org/document/9684649)

- **Weapon Detection Using YOLO V3 for Smart Surveillance** System(https://www.hindawi.com/journals/mpe/2021/9975700/)
- **Detecting Weapons using Deep Learning Model** (https://medium.com/@cloudgeek/detecting-weapons-using-deep-learning-model-7f7b409a250)
- **Weapons Detection for Security and Video Surveillance Using CNN and YOLO-V5s** (https://www.techscience.com/cmc/v70n2/44624)
- **Detection and Classification of Different Weapon Types Using Deep Learning** (https://www.mdpi.com/2076-3417/11/16/7535)

ANNEXURES

Key Terms and Definitions

- **Weapon Detection Technology:** Refers to the use of various methods and systems to identify and locate concealed or visible weapons in a particular area or environment.
- **Object Detection**: The process of identifying and localizing objects within an image or a video frame, including weapons, through the use of computer vision and machine learning algorithms
- **Thermal Imaging:** The use of specialized cameras to capture the heat emitted by objects and individuals, often employed in weapon detection systems to identify concealed weapons that may not be visible through traditional imaging techniques.
- **Millimeter Wave Scanning:** A technology that uses radio waves in the millimeter wave frequency range to create images of the scanned objects. This technique is commonly used in security screenings and weapon detection systems to identify metallic and non-metallic objects.
- **Security Infrastructure Integration:** The process of incorporating weapon detection systems into existing security frameworks and infrastructure, ensuring seamless coordination and operation with other security measures in a given environment.

Data Sets

Figure A. Screw driver images in the dataset

This is the folder which has screwdrivers images for identification and detection which is done by the model. There are various images with their annotations.

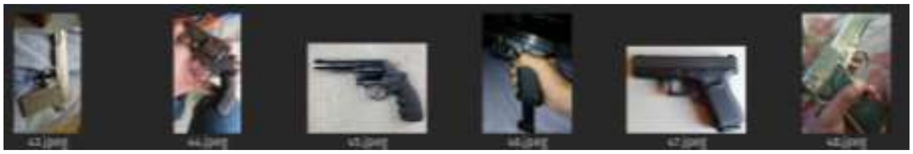

Figure B. Sample Dataset-2

This is the folder which has handguns, pistol and gun images for identification and detection which is done by the model. There are various images with their annotations.

Figure C. Sample Dataset-3

This is the folder which has handsaw images for identification and detection which is done by the model. There are various images with their annotations.

Coding Screenshots

Figure A. Metrics parameters graph of the model

This tensorflow dashboard visualizes the performance metrics graphs according to the model.

Figure B. Training parameters graph of the produced model

This tensorflow dashboard visualizes the performance training graphs according to the model.

Figure C. Training the model according to number of images and epochs

The small variant model have 55 epochs and extra-large variant model have 60 epochs for training phase.