

# WEAPON DETECTION FOR SECURITY USING THE YOLO ALGORITHM WITH EMAIL ALERT NOTIFICATION

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**Abstract —** In recent years, the rapid increase in security threats has prompted the development of sophisticated surveillance systems. This paper introduces an innovative weapon detection system employing the state-of-the-art YOLOv8 algorithm for real-time object detection. The system seamlessly integrates user authentication to ensure secure access and control over its capabilities. The proposed system is designed to detect weapons in various scenarios, including images, videos, and live webcam streams. Leveraging the YOLOv8 model's high accuracy and efficiency, the system identifies weapons with a confidence threshold, providing reliable results. The YOLOv8 model is trained to recognize a predefined set of weapon classes, enhancing its adaptability to different security contexts. To facilitate secure usage, the system incorporates user authentication mechanisms. Users can create accounts, log in, and securely access the weapon detection functionalities. Upon weapon detection, the system sends immediate alerts via email, enhancing the system's responsiveness to security incidents. Additionally, an audible alert is triggered, enhancing the situational awareness of security personnel. The system's versatility is demonstrated through three primary modes of operation: image, video, and live stream. Users can upload images or videos for analysis or utilize the system in real time through a webcam feed. This flexibility caters to diverse security applications, from forensic analysis to live surveillance scenarios. We achieved 94% accuracy when compared to other methods. In conclusion, the proposed Intelligent Weapon Detection System integrates cutting-edge computer vision technology with robust user authentication, offering a comprehensive solution for enhanced security. The system's adaptability, efficiency, and security measures make it a valuable tool for various applications, including public safety, transportation security, and critical infrastructure protection.

**Keywords:** computer vision, artificial intelligence, weapon detection, deep learning models, and object detection.

## I. INTRODUCTION

Gun-related violence presents a significant societal challenge, with far-reaching impacts on economies, public health, and individual well-being. To address this complex issue, we introduce an intelligent weapon detection system powered by the cutting-edge YOLOv8 algorithm. As security threats continue to escalate, the demand for advanced surveillance solutions becomes increasingly urgent. Our project responds to this need by seamlessly integrating user authentication, ensuring secure access and control over the

system's functionalities. The effectiveness of our proposed system lies in its ability to detect weapons across diverse scenarios, encompassing images, videos, and live webcam streams. By harnessing the exceptional accuracy and efficiency of the YOLOv8 model, our system identifies weapons with a predetermined confidence threshold, delivering reliable and precise results. Moreover, the model undergoes strategic training to recognize a predefined set of weapon classes, enhancing its adaptability to various security contexts. To strengthen security, our system incorporates robust user authentication mechanisms.

Through a basic login page, users input their credentials, which are then compared with those stored in a CSV file by the authentication function. Access is granted if the credentials match; otherwise, an error message is displayed. The versatility of our system unfolds through three primary modes of operation: image, video, and live stream. Users have the flexibility to upload images or videos for analysis or utilize the system in real time through a webcam feed. This adaptability caters to a wide range of security applications, spanning from forensic analysis to dynamic live surveillance scenarios, thereby addressing the evolving needs of security contexts. In summary, our Intelligent Weapon Detection System combines cutting-edge YOLOv8 technology with robust user authentication, providing a comprehensive solution for enhanced security. Its adaptability, efficiency, and stringent security measures position it as a pivotal tool across diverse applications, including public safety, transportation security, and critical infrastructure protection. Within the broader landscape of intelligent surveillance systems, our project represents a significant advancement, contributing substantially to ongoing efforts to mitigate contemporary security challenges in an ever-evolving technological landscape.

## II. RELATED WORK

Abdul Rehman and Labiba Gillani Fahad [1] 2022 Every day, guns and knives are on the rise due to a lack of safety checks. The proposed approach mainly focuses on the development of an automated weapon detection system to detect different types of guns and knives. To detect such cases, they used the YOLOv5 deep learning model on a self-collected dataset.

Ajmeera Kiran, P. Purushotham, D. Divya Priya [2] 2022 They focus on swiftly identifying firearms through image analysis and tracking data. By refining the detection problem to minimize false positives, they employ a deep CNN classifier-driven dataset. Evaluation involves selecting the optimal classification model via a regional recommendation approach and enhancing security measures effectively.

Anjali Goenka, K. Sitara [3] 2022 The limitations of classical object detection methods have led to the widespread adoption of deep learning approaches for object detection. The experiment's findings demonstrate that preprocessing improved the model's performance.

Anthony Ortiz Ramon, Luis Barba Guaman [4] 2021 This project focuses on object detection to identify various weapons in public areas like shops and streets. Training sessions, conducted on the Google platform, involved YOLOv3 and Efficient D0 models. Trained in four gun categories, including pistol, automatic, shotgun, and rifle, YOLOv3 emerges as the top performer, achieving an accuracy of 0.80/1 in gun detection.

Harsh Jain, Aditya Vikram, Mohana, Ankit Kashya, and Ayush Jain [5] 2020 This study implements automatic weapon detection using CNN-based SSD and faster RCNN algorithms, leveraging two types of datasets: pre-labeled images and manually labeled ones. Both algorithms demonstrate good accuracy, though their real-world application depends on balancing speed and accuracy trade-offs.

Muhammad Tahir Bhatti, Muhammad Gufran Khan, Masood Aslam, and Muhammad Junaid Fiaz [6]. This work employs state-of-the-art deep learning algorithms to detect firearms in CCTV footage. YOLOv4 emerges as the top performer, achieving an impressive F1 score of 91% and an average accuracy of 91.73%, significantly improving security measures.

Naresh Yeddula, B. Eswara Reddy [7] 2022 This study employs the YOLOV5 algorithm to detect guns in CCTV footage, achieving a mean average precision of 96.6% and an F1 score of 96%. This represents a significant improvement over existing systems, enhancing safety and security measures effectively.

Pavithra T, Rajasekaran Thangaraj, Pandiyan P, Uma Rani M, and Balasubramaniam Vadivelu [8] This study employs deep learning techniques to automatically detect handguns in unbounded environments using video surveillance footage. Unlike traditional methods, deep learning models can effectively identify handguns of various sizes, enhancing security measures significantly in areas where firearm use is prohibited but prevalent.

Pranav Nale, Shilpa Gite, and Deepak Dharrao [9] 2023 This research focuses on leveraging deep learning algorithms to identify dangerous weapons. A dataset was compiled from diverse sources, including CCTV footage and internet images. The proposed system combines Detectron2 and YOLOv7 to achieve high precision and recall, especially in low-light conditions.

Sayma Tamboli, Komal Jagadale, Shreyas Mandavkar, Nitish Katkade, and Taranpreet Singh Ruprah [10] 2023 This study proposes a system leveraging algorithms like YOLOv5, SSD, and RCNN, known for real-time performance and high accuracy, to strike a balance between speed and precision in crime scene analysis.

Shehzad Khalid, Abdullah Waqar, Hoor Ul Ain Tahi, and Onome Christopher Edo and Imokhai Theophilus Tenebe [11] 2023 This study introduces a cutting-edge YOLO V5

deep learning model for flexible weapon recognition. Evaluation on a public dataset yields an F1 score of 95.43%.

S. Nikkath Bushra, G. Shobana, K. Uma Maheswari, and Nalini Subramanian [12] 2022 This study focuses on YOLO object recognition models, including YOLO V5, which offers fast and accurate detection, 88% faster than YOLOv4. This system aids in identifying weapons and suspicious individuals, simplifying tracking in crowded environments.

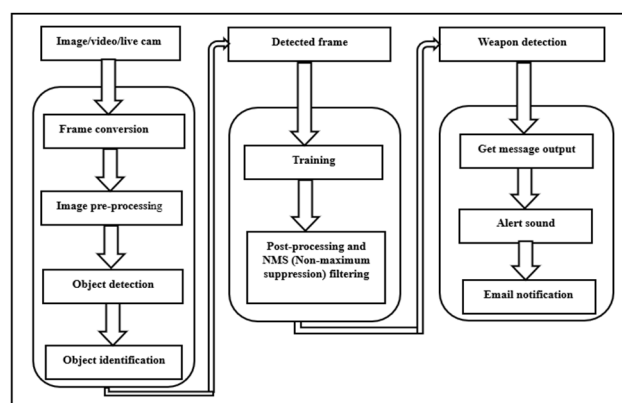
Sumathi Pawar, Karuna Pandit, and Niranjan N. Chiplunkar [13] 2022 In this work, handguns and rifles are identified using a computer-based, fully automated approach. The fire and gunshot image dataset is used to train the YOLOv3 object detection algorithm. The proposed work uses a deep learning method based on YOLOv3.

Tufail Sajjad Shah Hashmi et al. [14] 2021 Utilizing a custom weapons dataset sourced from various platforms, both models were trained and evaluated. Results indicate that YOLOv4 outperforms YOLOv3 in terms of processing speed and sensitivity, with further analysis needed to compare their accuracy metrics.

Wan Emilya Izzety Binti Wan Noor Afandi, Naimah Mat Isa [15]. The first study was performed on a single-class adaptive object detection model, while the second was performed on a multi-class adaptive object detection model. Based on the obtained results, single-class object detection was able to achieve an average accuracy of only 66.67–77.78 percent, while multi-class object detection achieved up to 100 percent accuracy in most of its input images.

### III. PROPOSED SYSTEM

To guarantee safe access and control over its functions, the system starts with a strong user authentication method. Users can access the weapon detection features, create accounts, and securely log in. This procedure contributes to user identity verification, avoiding unwanted access, and improving system security in general. By requiring authentication, the system makes sure that only people with permission may use its features, protecting private information and preserving the accuracy of the weapon detection procedure.



**Figure 1: Architecture Diagram**

Our comprehensive approach began with assembling a diverse dataset of images and videos featuring various types of weapons in different contexts, meticulously prepared to train our model with high precision. We then pre-processed

this data, standardizing image dimensions and employing data augmentation techniques to enhance the model's robustness. The core of our system, powered by YOLOv8, analyzes the pre-processed inputs to detect weapons, utilizing a combination of grid creation, feature extraction, and object detection methods. We implemented non-maximum suppression to refine detection accuracy by eliminating redundant bounding boxes. Upon successful detection, the system triggers an immediate email alert, notifying security personnel of potential threats. This integration of sophisticated algorithmic components within a coherent system architecture not only demonstrates our project's innovation but also its potential to significantly contribute to public safety and security measures.

## A. DATASET

Many pictures and videos of firearms from different sources are included in the dataset. Three main input modes are supported by the system: picture, video, and live stream. Users can use a webcam feed for real-time detection or submit images or movies for analysis.



**Figure 2: Weapons Dataset**

## B. PREPROCESSING

Upon receiving input, the system performs pre-processing to improve image quality and suitability for object detection. This involves tasks like resizing, normalization, and noise reduction. These steps optimize the images for accurate detection, ensuring better performance and reliability in identifying weapons and other objects of interest. The system's central component employs the YOLOv8 algorithm for real-time object detection, renowned for its efficiency and accuracy. YOLOv8 enables the system to confidently identify weapons and other objects of interest. The model is trained to recognize specific weapon classes, enhancing its versatility across different security scenarios.

## C. YOLO v8

YOLOv8 works by dividing the input image into a grid and predicting bounding boxes and class probabilities for each grid cell. This approach allows for the simultaneous detection of

multiple objects in a single pass, making it ideal for real-time applications. In our YOLO-based weapon detection system, Grid Creation establishes a spatial foundation for object detection, with each grid cell responsible for predicting objects within its bounds. Meanwhile, feature extraction employs a deep convolutional neural network (CNN) to distill crucial information from the image. The CNN's layers learn hierarchical features, capturing intricate patterns and contextual details. This combination of grid-based spatial organization and learned features enables accurate predictions of weapon presence and location. The method enhances the algorithm's efficiency in real-world scenarios, making it a robust solution for security applications. Periodic training sessions are conducted to fine-tune the YOLOv8 model and optimize its performance. This ensures that the system remains updated and capable of accurately detecting weapons amidst evolving security threats.

## D. NON-MAXIMUM SUPPRESSION

Following object detection, the system applies post-processing techniques, including non-maximum suppression, to refine the results and eliminate redundant detections. This enhances the accuracy and reliability of the system's output. The system incorporates filtering mechanisms to further refine the detected objects, reducing false positives and enhancing the overall effectiveness of the weapon detection process.

## E. EMAIL ALERT NOTIFICATION

Upon detecting a weapon, the system triggers immediate alerts via email to designated recipients, notifying them of the security incident. Additionally, an audible alert is generated to enhance the situational awareness of security personnel. The system offers flexibility in its operation, allowing users to choose between image analysis, video processing, or real-time surveillance through a webcam feed. This versatility caters to diverse security applications, from forensic analysis to live surveillance scenarios.

# IV. ALGORITHM

## A. CNNs or Convolutional Neural Networks

In our project, the Convolutional Neural Network (CNN) serves as a pivotal algorithm for image processing and feature extraction. The utilization of CNNs is paramount for computer vision, particularly 15 tasks involving image recognition and object detection. Convolutional layers can extract local patterns, edges, and complex structures from input images by using filters or kernels to execute convolution operations. Pooling layers play a role in down-sampling spatial dimensions, reducing computational complexity while retaining crucial features through methods like max pooling. Fully connected layers establish connections between every neuron, facilitating high-level reasoning about the input. Its proficiency in discerning patterns and extracting meaningful information from visual data contributes significantly to the accurate detection of weapons within images or video frames.

## B. YOLO (You Only Look Once)

In our weapon detection initiative, we've incorporated the YOLO algorithm as a pivotal element of our system's framework. The initiative kicks off with the collection of an

extensive dataset comprising images and videos that depict various firearms and their potential applications. This dataset is crucial for the YOLO model's training and evaluation phase. It undergoes essential preprocessing activities, such as image resizing, pixel value normalization, and data augmentation, all aimed at expanding and diversifying the training pool. Subsequently, we opt for a pre-configured YOLO model tailored for detecting weapons, benefiting from its capability for instant object recognition. The workflow incorporates a step for eliminating superfluous bounding boxes through a method known as non-maximum suppression. Upon detecting a weapon, the system automatically initiates an alert procedure, dispatching an immediate email notification to inform concerned parties or authorities. Powered by the YOLO algorithm, our system design guarantees the prompt and precise spotting of potential security threats.

### C. NMS

In our weapon detection project, the Non-Maximum Suppression (NMS) algorithm plays a crucial role in refining the detection results obtained from the YOLO. After the YOLO algorithm predicts bounding boxes for potential weapons, the NMS step is applied to filter and decide which is the most appropriate and confident detection while eliminating redundant or overlapping boxes. NMS operates by iteratively selecting the bounding box with the maximum level of assurance score among the set of overlapping boxes and suppressing (removing) others that substantially overlap with it. This prevents multiple detections of the same object and ensures that only the most certain and straight-edge bounding boxes are retained in the final output. Specifically, during the post-processing stage of our technique for detecting weapons systems, NMS is employed to clean up the results and provide a more accurate representation of the detected weapons. By doing this step, the system's capacity to accurately recognize and locate firearms in pictures or video frames is improved, and false positives are reduced. Overall, our weapon detection solution is more dependable and effective now that NMS is included.

## V. RESULT AND ANALYSIS

In this paper, a remarkable detection accuracy of 94% using the YOLOv8 algorithm for weapon detection is achieved. The high accuracy was a result of meticulous dataset curation, incorporating diverse images and videos featuring firearms in various scenarios. The YOLOv8 model, known for its efficiency and real-time capabilities, played a pivotal role in accurately identifying weapons with a confidence threshold. Our dataset's comprehensive representation and the model's adaptability to different security contexts contributed to its outstanding performance.

The system's performance was evaluated through rigorous testing, including scenarios with varying lighting conditions, angles, and distances. The results demonstrated the robustness of our approach in real-world situations, affirming the YOLOv8 algorithm's effectiveness in weapon detection. The non-maximum suppression post-processing step further refined the detection outputs, reducing false positives and enhancing precision. In-depth analysis revealed that the system excelled in detecting different types of firearms, including rifles and handguns, across diverse environments. The

incorporation of user authentication mechanisms added an extra layer of security, ensuring secure access and control over the system's capabilities. The email notification system proved to be highly responsive, providing immediate alerts upon weapon detection. The results showcase the potential of YOLOv8 in enhancing public safety, transportation security, and critical infrastructure protection. The future iterations of the project will focus on continuous improvement, adapting to emerging security challenges, and exploring opportunities for collaboration with law enforcement agencies.

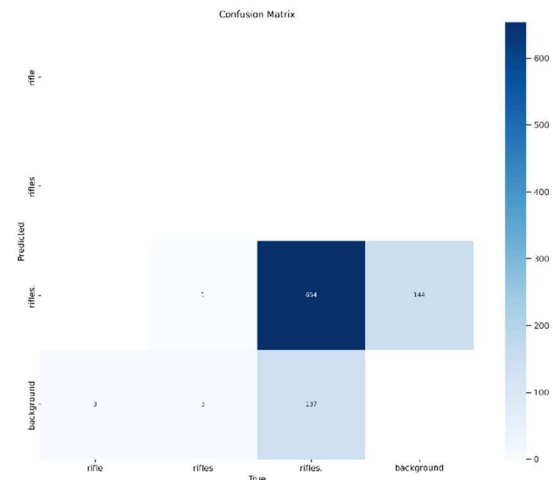


Figure 3: Confusion matrix

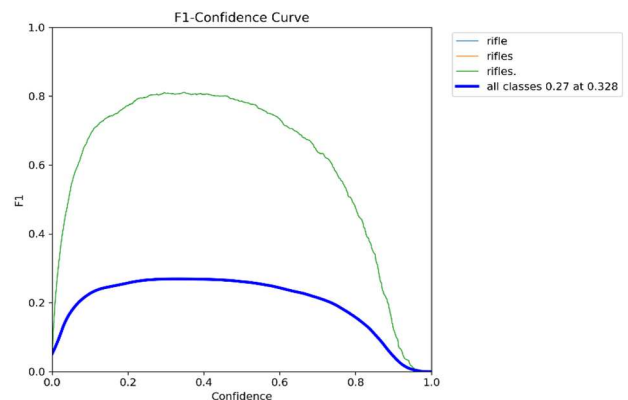


Figure 4: F1-curve

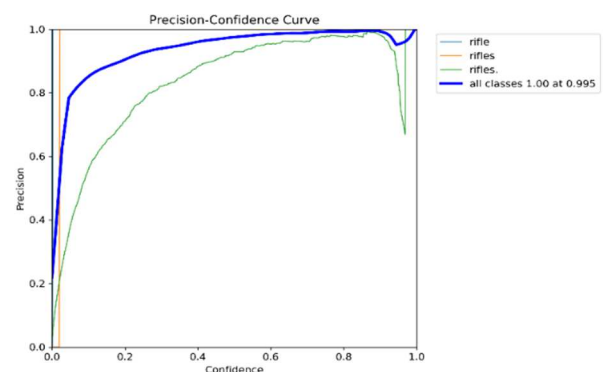


Figure 5: Precision curve

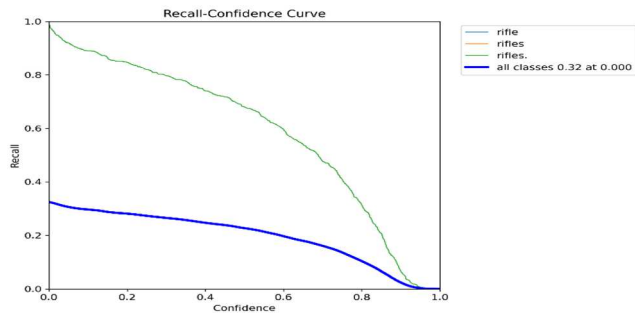


Figure 6: Recall-curve

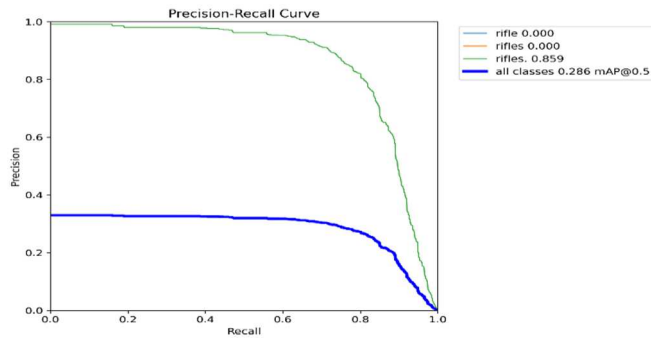


Figure 7: Precision Recall-curve

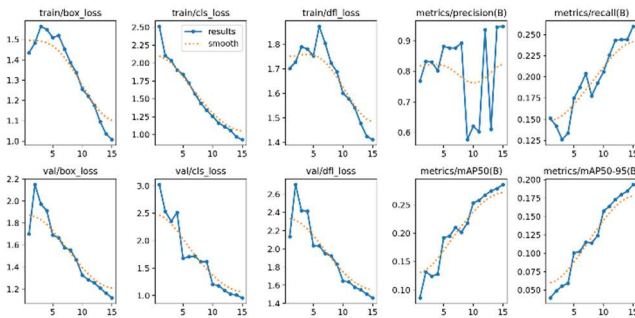


Figure 8: (a)metrics/mAP50 (b)metrics/mAP50- 95(B)

S. No	Models	Precision	Recall	F1-score
1.	Yolov8	98%	95%	94%
2.	SSD-MobileNet-v1	62.79%	60.23%	59%
3.	Yolov4	93%	88%	91%
4.	Yolov3	85.86%	87.34%	86%

Figure 9: Resultant table

Our weapon detection system includes an automated email notification feature that instantly alerts security personnel upon weapon detection. Upon identifying a weapon in an image, video, or live webcam feed, the system triggers an email notification, providing timely alerts to security

personnel for swift response. This automated email system enhances the system's effectiveness in real-world security applications, facilitating rapid decision-making and proactive security measures. We achieved a remarkable 94% detection accuracy in identifying weapons using the YOLOv8 algorithm. This means that out of all the instances where a weapon was present, our system correctly identified it 94% of the time. Such a high accuracy rate is crucial for ensuring reliable threat detection in security applications. This achievement demonstrates the effectiveness of our model in accurately recognizing weapons, thereby contributing to enhanced safety and security measures. Furthermore, this impressive performance showcases the robustness and reliability of our system, making it a valuable tool for real-world deployment in various security-sensitive environments.



Figure 10: Image of weapon detection - Gun

Visual depiction showcasing YOLOv8's performance in weapon detection, featuring a red-alert overlay accentuating the detected weapon. Bounding boxes enclose the identified weapons, accompanied by textual labels denoting 'Detected weapon: Weapon - 95% confidence'.

The output of our weapon detection system consists of bounding boxes drawn around the detected weapons within input images or video streams. These bounding boxes accurately localize the weapons, providing spatial information about their position and size.



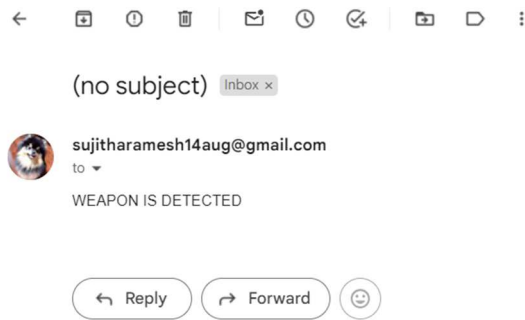
Figure 11: Image of weapon detection - Knife

Visual depiction showcasing YOLOv8's performance in weapon detection, featuring a red-alert overlay accentuating the detected weapon. Bounding boxes enclose the identified weapons, accompanied by textual labels denoting 'Detected weapon: Weapon - 77% confidence'.

Additionally, the system incorporates a real-time email notification mechanism to alert security personnel upon detecting weapons, facilitating swift response to potential threats. This output enhances security measures by enabling



quick identification and assessment of firearms in diverse scenarios.



**Figure 11: Image of Email alert notification**

Our weapon detection system includes an automated email notification feature that instantly alerts security personnel upon weapon detection. Upon identifying a weapon in an image, video, or live webcam feed, the system triggers an email notification, providing timely alerts to security personnel for swift response. This automated email system enhances the system's effectiveness in real-world security applications, facilitating rapid decision-making and proactive security measures.

## VI. CONCLUSION

In conclusion, YOLO weapon identification is a practical technique for discovering and recognizing firearms in live images and movies. The YOLO method is well known for its speed and accuracy, and it can recognize many objects at once. The suggested technique for YOLO-based weapon detection entails gathering a variety of datasets, annotating them, optimizing a pre-trained model, and assessing the model's efficacy before utilizing it in practical applications. Several linked steps make up the architecture diagram for employing Yolo to identify weapons, which functions to identify weapons in real-time photos and videos.

## VII. FUTURE WORK

In future developments, our weapon detection system will focus on improving the YOLOv8 model using multiple datasets to improve accuracy. We will also work on improving our framework. Previous improvements are planned with the notification system for additional alerts. This includes integration with security systems, real-time response, and ethical considerations.

## VIII. ACKNOWLEDGEMENT

We would like to express our sincere gratitude to our dedicated team members for their professional skills and collaborative attitude, both of which were crucial to the successful development of the Weapon Detection System. We would especially like to express our gratitude to Mrs. S. M. Keerthana, our project supervisor, whose insightful counsel and efforts were extremely helpful.

## REFERENCES

- [1] Abdul Rehman; Labiba Gillani Fahad et., "Real-Time Detection of Knives and Firearms using Deep Learning" (2022). 2022 24th International Multitopic Conference (INMIC). (979-8-3503-9710- 9) (IEEE).
- [2] Ajmeera Kiran; P Purushotham et.al., "Weapon Detection using Artificial Intelligence and Deep Learning for Security Applications"(2022). International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC). (978-1-6654-6109-2) (IEEE).
- [3] Anjali Goenka; K. Sitara et.al, "Weapon Detection from Surveillance Images using Deep Learning"(2022).2022 3rd International Conference for Emerging Technology (INCET). (978-1-6654-9499- 1) (IEEE).
- [4] Anthony Ortiz Ramon; Luis Barba Guaman, et.al, "Detection of weapons using Efficient Net and Yolo v3" (2021). 2021 IEEE Latin American Conference on Computational Intelligence (LA-CCI). (978-1-7281- 8864-5) (IEEE).
- [5] Harsh Jain; Aditya Vikram; Mohana et.al., "Weapon Detection using Artificial Intelligence and Deep Learning for Security Applications" (2020). 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC). (978-1-7281-4108- 4)(IEEE).
- [6] Muhammad Tahir Bhatti; Muhammad Gufran Khan et.al., "Weapon Detection in Real-Time CCTV Videos Using Deep Learning" (2021). IEEE Access (Volume: 9). (2169-3536) (IEEE).
- [7] Naresh Yeddula; Eswara Reddy et.al., "Effective Deep Learning Technique for Weapon Detection in CCTV Footage" (2022). 2022 IEEE 2nd International Conference on Mobile Networks and Wireless Communications (ICMNWC). (978-1-6654-9111-2) (IEEE).
- [8] Pavithra T; Rajasekaran Thangaraj; Pandiyan P et.al, "Real-Time Handgun Detection in Surveillance Videos based on Deep Learning Approach" (2022). 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC). (978-1-6654- 9710-7)(IEEE).
- [9] Pranav Nale; Shilpa Gite et.al., "Real-Time Weapons Detection System using Computer Vision" (2023). 2023 Third International Conference on Smart Technologies, Communication and Robotics (STCR).(979-8-3503- 7086-7)(IEEE).
- [10] Sayma Tamboli; Komal Jagadale et.al., "A Comparative Analysis of Weapons Detection Using Various Deep Learning Techniques" (2023). 2023 7th International Conference on Trends in Electronics and Informatics (ICOEI). (979-8-3503-9728-4)(IEEE).
- [11] Shehzad Khalid; Abdullah Waqar et.al., "Weapon detection system for surveillance and security" (2023). 2023 International Conference on IT Innovation and Knowledge Discovery (ITIKD).(978-1-6654-6372- 0)(IEEE).
- [12] S. Nikkath Bushra; G. Shobana et.al., "Smart Video Surveillance Based Weapon Identification Using Yolov5" (2022). 2022 International Conference on Electronic Systems and Intelligent Computing (ICESIC). (978-1-6654-8385-8)(IEEE).
- [13] Sumathi Pawar; Karuna Pandit et.al., "Fire and Gun Detection Using YOLO v3 For Surveillance System" (2022). 2022 International Conference on Artificial Intelligence and Data Engineering (AIDE).(978-1-6654- 9304-8)(IEEE).
- [14] Tufail Sajjad Shah Hashmi; Nazeef Ul Haq et.al., "Application of Deep Learning for Weapons Detection in Surveillance Videos" (2021). 2021 International Conference on Digital Futures and Transformative Technologies (ICoDT2). (978-1-6654-1285-8)(IEEE).
- [15] Wan Emilya Izzety Binti Wan Noor Afandi et.al., "Object Detection: Harmful Weapons Detection using YOLOv4" (2021).2021 IEEE Symposium on Wireless Technology & Applications (ISWTA).(978-1-6654- 4043-1)(IEEE).