Real-time Detection of Deadly Weapons and Enhancing Public Safety using YOLOv5 with Alert System

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I. INTRODUCTION

In 2016, gun-related incidents globally surpassed 250,000, with over 1,013,000,000 firearms, mainly in civilian hands (N. Kurek, L. A. Darzi and J. Maa, 2020).. Real-time processing and fast response times are crucial for weapon detection systems, necessitating research to enhance processing speed. Challenges like similar shapes of non-weapon objects lead to high false negatives and false positives. Detecting weapons accurately while avoiding false alarms is critical, especially in videos where existing models struggle. To address these issues, this study proposes a model leveraging fast detection speeds of modern techniques like YOLOv5. The key contribution lies in reducing false positives and negatives in weapon detection, expanding the range to include rifles (R. Olmos, S. Tabik and F. Herrera.,2018).

Traditional weapon detection systems using sensors are expensive, insecure, and inefficient, often unable to cover large surveillance areas. To address these limitations, machine learning algorithms, particularly the YOLO (You Only Look Once) algorithm, have been deployed. Unlike sensors, YOLO analyzes entire input images, simplifying the detection process. It highlights regions of interest with bounding boxes, enhancing real-time detection accuracy. YOLO, especially the YOLOv5 algorithm, enables easy detection of illegal activities, particularly in crowded areas. It identifies both high and low-level objects like weapons and unusual items, improving security measures significantly (Mukto, M., et al, 2024).

II. BACKGROUND OF THE STUDY

Crime is difficult to predict in advance, but signs of potential criminal activity can be observed by monitoring suspect behavior and surroundings. Surveillance cameras are commonly used to monitor individual activities for any abnormal or criminal incidents in an area. These cameras transmit captured videos over IP networks for security personnel to view. However, continuous, and careful monitoring by security personnel is necessary to identify unusual incidents in a timely manner. This monitoring can be laborious and have negative effects on mental health. Therefore, there is a need for automated systems that utilize machine learning and artificial intelligence to monitor human actions and predict the occurrence of crime incidents before they happen (Motiian et al., 2017).

Gun and knife-related incidents are rising due to insufficient security checks. While CCTV cameras are being installed in many places, constant surveillance is challenging for humans. There is a pressing need for automated weapon detection to curb these incidents. The proposed solution aims to develop an automated system using YOLOv5 deep learning model to detect firearms and knives. This system is designed to enhance security measures and prevent potential threats more effectively [2].

III. STATEMENT OF THE PROBLEM

Public safety is a concern from schools, workplaces, and public spaces. The presence of deadly can turn a situation dangerous putting lives at risk. Traditional methods of weapon detection often rely on physical checks or surveillance footage review. These methods are important, but it has limitations, Physical check can be time consuming, while footage review can lead to delays in identifying threats. This is concerning in crowded environments where immediate action is important. Unlike traditional methods, TANAW incorporates a weapon detection model built upon YOLOv5. This model allows for real-time identification of a variety of deadly weapons, including firearms and knives, this eliminates the delays associated with physical check or video review.

This allows for a faster response to potential threat, saving lives, and preventing dangerous situations from escalating.

The system integrates an automated alert system that triggers instantly upon identifying weapon. This notification system directly informs the barangay to allow security officers to intervene quickly.

IV. OBJECTIVES

This research aimed to create a Detection of Deadly Weapons and Enhancing Public Safety using YOLOv5 with Alert System

1. Develop and Implement a Real-Time Weapon Detection System Based on YOLOv5.
2. Enhance Public Safety and Security Measures Through Automated Weapon Detection and Immediate Alert Systems.

V. RELATED STUDIES

Researchers (Grega et al., 2016) built algorithms to automatically detect dangerous situations in CCTV footage, like spotting knives and guns held in hands. Their knife detection was especially good at finding these weapons (high sensitivity) while rarely mistaking other objects for them (high specificity). It even worked well on grainy videos. While the gun detection was very good at not raising false alarms (high specificity) for non-dangerous situations, it sometimes missed actual guns (lower sensitivity) in videos with dangerous objects. They're working on improving these algorithms to work better in different situations, combine them, and reduce false alarms. They also want to add new ways to identify dangerous tools in difficult conditions, ultimately creating a complete system for CCTV operators.

According to Olmos et al. (2018), an innovative automatic handgun detection system designed for surveillance and control purposes addresses the issue of false positives by leveraging deep Convolutional Neural Networks (CNNs). By refining the detection problem and training data based on CNN classifier results, the researchers evaluated different classification models using sliding window and region proposal approaches. The most promising results were achieved with a Faster R-CNN-based model trained on their new database, showing potential even in low-quality videos like those on YouTube and functioning effectively as an automatic alarm system. The study also introduced a new metric, Alarm Activation Time per Interval (AATpI), to evaluate detection model performance in real-time video surveillance scenarios.

Dwivedi et al. (2019) focuses on weapon detection and classification using video surveillance to enhance public safety, particularly in places like schools and malls. The researchers propose two new deep CNN architectures based on the VGG16 model, fine-tuned by training them with images of knives, guns, and no-weapons classes. They achieved a maximum accuracy of 98.41% with Model A using a 0.5 dropout rate, highlighting the effectiveness of their approach. Interestingly, they found that simply increasing the number of neurons doesn't always improve accuracy; Model A with fewer neurons outperformed Model B with a higher dropout rate in fully connected layers. This study underscores the importance of optimizing model architecture and dropout rates for accurate weapon detection in real-time scenarios,

VI. METHODOLOGY

This section outlines for developing a real-time gun and knife detection. The methodology includes Dataset collection, Image Annotation and Augmentation, YOLOv5 Model Training and Evaluation, and Deployment. The other procedures expound about public dataset gaining, custom dataset creation, image annotation using Roboflow, YOLOv5 model training and configuration, evaluation with false positive/negative analysis, image augmentation, addressing class imbalance and hyperparameter tuning, different training epochs, and deployment for real-time video processing.

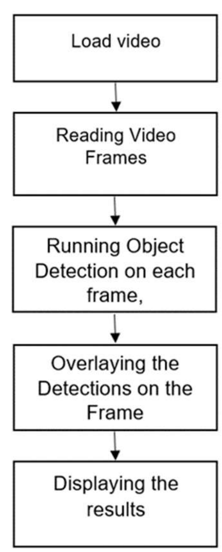


Figure 1: Program Flow for Guns and Knives

A. Dataset Collection

The researchers searched for publicly available image sets containing guns and knives in various settings, including viewpoints, lighting, and backgrounds. This ensured the system could adapt to real-world scenarios under different conditions. A custom dataset with images and videos specific to the barangay was created to further enhance the model and capture local weapons. Maintaining a balanced representation of different weapon types within the dataset was essential.

B. Image Annotation and Augmentation

Researchers used Roboflow to label each weapon instance in the images with bounding boxes. This process was like circling the weapons in a photo lineup. The accuracy of these labels was essential for training the program to recognize weapons effectively.

Figures 2-5: Dataset Collection

C. YOLOv5 Model Training and Evaluation:

The researchers used YOLOv5 to identify guns and knives in videos. The videos combined the public and custom datasets collected. Then, the combined data was split into training, validation, and testing. During training, YOLOv5 was taught to recognize weapons using training data. Based on this data, an optimization algorithm was employed to improve the model's internal settings. Validation data was essential to improve the training process and prevent overfitting by monitoring the model's performance and adjusting the learning rate and training epochs (100, 200, and 300). Testing data evaluated YOLOv5's accuracy in detecting weapons and avoiding errors like mistaking harmless objects for real weapons. Metrics such as precision, recall, F1-score, and false positives/negatives were used for evaluation.

D. Deployment

The final stage included deploying the trained program for real-time usage through a structured video processing pipeline. This involved initializing the YOLOv5 model, capturing video, and setting necessary parameters. Each video frame was read, resized, and preprocessed for efficient processing, followed by predicting weapons within a specific area of interest (ROI) in the frame, focusing on areas with a higher likelihood of weapons presence, such as building entrances. Detected weapons were annotated on the frame for clear visualization, and the processed video stream with weapon annotations overlaid was displayed, allowing real-time monitoring. Deployment is required to ensure the hardware can handle real-time video processing with YOLOv5 for efficient operation.

VII. RESULT AND DISCUSSIONS

a. Modeling Training and Evaluation Results

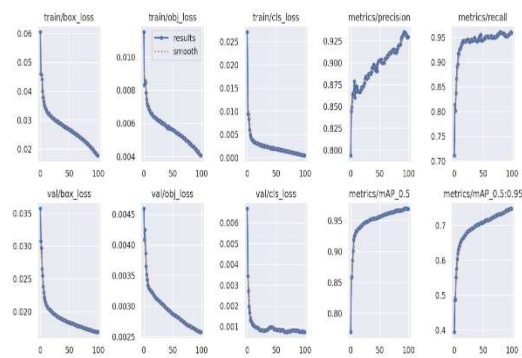
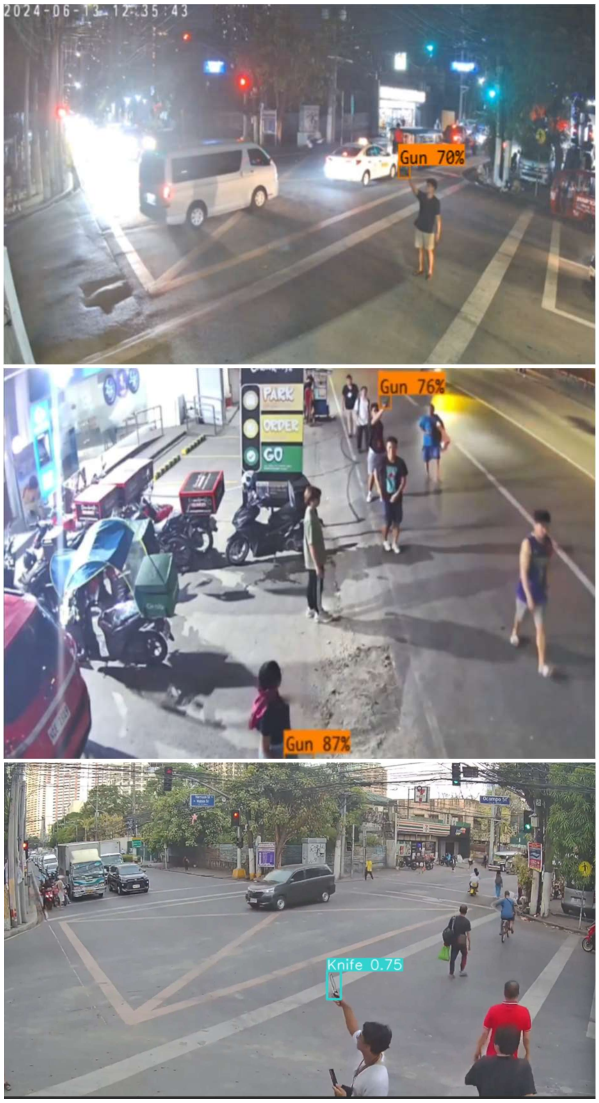


Figure 6: Training and Evaluation Results Chart

Over 100 epochs, the model demonstrated significant improvements in training and validation metrics. Training box loss decreased from 0.06 to 0.02, object loss from 0.010 to 0.004, and classification loss from 0.025 to nearly 0, indicating enhanced accuracy in predicting bounding boxes, detecting objects, and classifying them correctly. Precision improved from 0.800 to 0.925 and recall from 0.70 to 0.95. Validation metrics showed similar trends, with box loss decreasing from 0.035 to 0.020, object loss from 0.0045 to 0.0025, and classification loss from 0.006 to 0.001. The mean average precision (mAP@0.5) increased from 0.80 to 0.95, while mAP@0.5:0.95 rose from 0.4 to 0.7, reflecting ongoing improvements in performance across various IoU thresholds.

b. Video and Image Detection



Figures:7-9: Guns and Knives Detection

Table 1. Taft Avenue - P. Ocampo St. Camera Detection Trials

	DISTANCE (m)	GUNS AND KNIVES STATUS
TRIAL 1	3.00m	DETECTED
TRIAL 2	3.40m	DETECTED
TRIAL 3	3.70m	DETECTED
TRIAL 4	4.00m	DETECTED
TRIAL 5	4.40m	DETECTED
TRIAL 6	4.70m	DETECTED
TRIAL 7	5.00m	DETECTED
TRIAL 8	5.40m	DETECTED
TRIAL 9	5.70m	DETECTED
TRIAL 10	6.00m	DETECTED
TRIAL 11	6.40m	DETECTED
TRIAL 12	6.70m	DETECTED
TRIAL 13	7.00m	DETECTED
TRIAL 14	7.40m	DETECTED
TRIAL 15	7.70m	DETECTED
TRIAL 16	8.00m	DETECTED
TRIAL 17	8.40m	DETECTED
TRIAL 18	8.70m	DETECTED
TRIAL 19	9.00m	DETECTED
TRIAL 20	9.40m	DETECTED
TRIAL 21	9.70m	DETECTED
TRIAL 22	10.00m	DETECTED
TRIAL 23	10.40m	DETECTED
TRIAL 24	10.70m	DETECTED
TRIAL 25	11.00m	DETECTED
TRIAL 26	11.40m	DETECTED
TRIAL 27	11.70m	DETECTED
TRIAL 28	12.00m	DETECTED
TRIAL 29	12.40m	DETECTED
TRIAL 30	12.70m	UNDETECTED

Table 2. P. Ocampo St. – A. Mabini St. Camera Detection Trials

	DISTANCE (m)	GUNS AND KNIVES STATUS
TRIAL 1	3.00m	DETECTED
TRIAL 2	3.40m	DETECTED
TRIAL 3	3.70m	DETECTED
TRIAL 4	4.00m	DETECTED
TRIAL 5	4.40m	DETECTED
TRIAL 6	4.70m	DETECTED
TRIAL 7	5.00m	DETECTED
TRIAL 8	5.40m	DETECTED
TRIAL 9	5.70m	DETECTED
TRIAL 10	6.00m	DETECTED
TRIAL 11	6.40m	DETECTED
TRIAL 12	6.70m	DETECTED
TRIAL 13	7.00m	DETECTED
TRIAL 14	7.40m	DETECTED
TRIAL 15	7.70m	DETECTED
TRIAL 16	8.00m	DETECTED
TRIAL 17	8.40m	DETECTED
TRIAL 18	8.70m	DETECTED
TRIAL 19	9.00m	DETECTED
TRIAL 20	9.40m	DETECTED
TRIAL 21	9.70m	DETECTED
TRIAL 22	10.00m	DETECTED
TRIAL 23	10.40m	DETECTED
TRIAL 24	10.70m	DETECTED
TRIAL 25	11.00m	DETECTED
TRIAL 26	11.40m	DETECTED
TRIAL 27	11.70m	DETECTED
TRIAL 28	12.00m	DETECTED
TRIAL 29	12.40m	DETECTED
TRIAL 30	12.70m	UNDETECTED

Table 3. P. Ocampo St. - F.B. Harrison St. Camera Detection Trials

	DISTANCE (m)	GUNS AND KNIVES STATUS
TRIAL 1	4.00m	DETECTED
TRIAL 2	4.25m	DETECTED
TRIAL 3	4.50m	DETECTED
TRIAL 4	4.75m	DETECTED
TRIAL 5	5.00m	DETECTED
TRIAL 6	5.25m	DETECTED
TRIAL 7	5.50m	DETECTED
TRIAL 8	5.75m	DETECTED
TRIAL 9	6.00m	DETECTED

TRIAL 10	6.25m	DETECTED
TRIAL 11	6.50m	DETECTED
TRIAL 12	6.75m	DETECTED
TRIAL 13	7.00m	DETECTED
TRIAL 14	7.25m	DETECTED
TRIAL 15	7.50m	DETECTED
TRIAL 16	7.75m	DETECTED
TRIAL 17	8.00m	DETECTED
TRIAL 18	8.25m	DETECTED
TRIAL 19	8.50m	DETECTED
TRIAL 20	8.75m	DETECTED
TRIAL 21	9.00m	DETECTED
TRIAL 22	9.25m	DETECTED
TRIAL 23	9.50m	DETECTED
TRIAL 24	9.75m	DETECTED
TRIAL 25	10.00m	DETECTED
TRIAL 26	10.25m	DETECTED
TRIAL 27	10.50m	DETECTED
TRIAL 28	10.75m	DETECTED
TRIAL 29	11.00m	DETECTED
TRIAL 30	11.25m	UNDETECTED

The figure shows that the camera at Taft Avenue and P. Ocampo St. has a detection range of 12.60 meters. The camera at P. Ocampo St. and F.B. Harrison St. offers a maximum detection range of 11.05 meters, while the camera at the intersection of P. Ocampo St. and A. Mabini St. has a maximum detection range of 8.53 meters. These cameras demonstrate advanced capabilities in detecting weapons both during the day and in low-light nighttime conditions. The figures highlight the system's resilience and accuracy in challenging environments, underscoring its robust performance in real-time incident detection and monitoring. The clear demonstration of the camera's effectiveness in capturing critical details under adverse lighting conditions emphasizes its reliability and effectiveness in enhancing public safety.

c. Alert System Notification and Live Feed

Table 4. Delay in Video Processing at Different Resolutions and Frame Rates

Parameter	Values		Delay (ms)		
			Video Stream	ML Output	ML Video Stream
Capture Resolution	2560x1440	15fps	1000	70	7000

The table shows that capturing video at higher resolutions with moderate frame rates causes a 1000 ms delay. Machine learning processing is quicker, with only a 70 ms delay. However, when applied to video streams, machine learning shows a significant 7-second delay due to its complexity.

Table 5. Real-Time Event Processing Latency

Real-time Event	Data Sent	
	ML-to- DB	DB-to-ML
	40 ms	800 ms

The table presents the latency in milliseconds for different stages of processing real-time events in a system, precisely the period taken for data to be sent from the machine learning (ML) to the database (DB) with 40 ms and then from the database to email notifications with 800 ms.

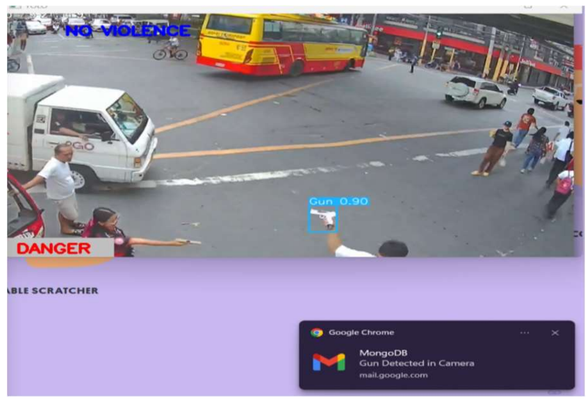


Figure 10: Visual and Audio Alert using Push Notification

The figure represents the alert system operation through email notifications and push notifications, which include an audio alert accompanying the pop-up notification.

VIII. CONCLUSION

The TANAW system is a real-time monitoring and detection specifically for deadly weapons, utilizing the YOLOv5 algorithm for identification and an alert system for notifications. The hardware includes ESP32, IP Camera C320WS, and a power management system. The YOLOv5 algorithm effectively identifies weapons like guns and knives, and the alert system promptly notifies relevant authorities. The system is monitored through a website hosted on AWS and MongoDB cloud service.

Testing involved collaboration with traffic enforcers and barangay officials, adhering to ISO 9126 standards. Evaluation metrics, such as the confusion matrix, F1 confidence curve, precision-recall curve, and training/validation metrics, demonstrate the system's accuracy and improvement over epochs. The system achieved high precision

(0.929), recall (0.959), mAP@50 (0.969), and mAP@50-95 (0.884).

Camera detection ranges were analyzed, with cameras at Taft Avenue and P. Ocampo St., P. Ocampo St. and F.B. Harrison St., and P. Ocampo St. and A. Mabini St. having detection ranges of 12.60 meters, 11.05 meters, and 8.53 meters, respectively. TANAW is suitable for community use and enhances public safety by effectively detecting deadly weapons in both day and nighttime conditions.

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