Real-Time Human and Handgun Detection Using YOLOv8

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***Abstract*—We propose a dual-object detection system using YOLOv8 for real-time person and handgun detection. The system utilizes two distinct YOLOv8 models: one pre-trained on the COCO dataset for person detection and another custom-trained for handgun detection. To improve the model's performance, we enhance the YOLOv8 architecture with custom convolutional neural network (CNN) layers and attention mechanisms. The custom CNN layers aim to extract richer features, while the attention layers (SEBlock) focus on refining the most informative features from the model's output. This combined approach is evaluated for its accuracy and speed in a real-time video stream scenario, where it detects and classifies persons and handguns with high confidence. The system demonstrates practical applications in security surveillance, where accurate and efficient object detection is essential.**

***Index Terms*—YOLOv8, Person Detection, Gun Detection, Attention Mechanism, Real-time Detection, Object Detection, Security Surveillance, Computer Vision**

I. Introduction

Object detection has emerged as a critical component in computer vision, enabling a wide range of applications, from autonomous driving and robotics to security and surveillance. In high-stakes scenarios such as public safety and crisis management, real-time detection of specific objects, such as persons and weapons, plays a pivotal role in mitigating risks and responding effectively to potential threats. This paper presents a novel approach for the real-time detection of persons and handguns using the YOLOv8 architecture. The YOLOv8 model, known for its speed and accuracy, has been leveraged in two distinct configurations: a pre-trained model for person detection and a custom-trained model for handgun detection. To further enhance detection performance, custom convolutional neural network (CNN) layers and attention mechanisms have been integrated into the YOLOv8 architecture. The addition of CNN layers allows for deeper feature extraction, while the attention mechanism focuses on the most relevant features, improving the model's accuracy in identifying small and occluded objects.

The proposed system is evaluated in a real-time video stream scenario, such as those captured by surveillance cameras. By combining the strengths of YOLOv8 with advanced architectural enhancements, the system achieves high precision and confidence in detecting persons and handguns simultaneously. This makes it a valuable tool for security, law enforcement, and public safety applications.

The remainder of this paper is organized as follows: The Literature Survey section reviews related work in object detection and custom model enhancements; the System Model and Problem Formulation section details the architectural and algorithmic contributions; the Performance Evaluation section discusses the experimental setup and results; and finally, the Conclusion section summarizes the findings and outlines potential future directions.

II. Literature Survey

Kumar et al. explore the use of YOLOv4 for real-time person detection in surveillance systems. The paper argues that YOLOv4 provides a high degree of accuracy and speed in real-time environments. The study compares YOLOv4 with other CNN-based detection algorithms, demonstrating that YOLOv4 is effective in identifying people in crowded environments with low latency. However, the study acknowledges challenges in detection accuracy when people are partially occluded or in complex lighting conditions. The research aims to improve robustness through further fine-tuning of the YOLOv4 model [1].

Nguyen et al. investigate the application of YOLOv5 for real-time firearm detection in public spaces. The paper highlights the increasing importance of automated surveillance systems for security purposes. They found that YOLOv5 outperforms earlier versions (YOLOv3 and YOLOv4) in terms of speed and accuracy for detecting firearms. The paper discusses challenges such as detecting handguns in cluttered backgrounds and addresses the need for a large, annotated dataset to improve the model's performance in real-world conditions [2].

Lee et al. present a modification of YOLOv3 for detecting persons and weapons, specifically focusing on handguns in

urban surveillance. The paper addresses challenges such as detecting small objects (weapons) and individuals in dense environments. YOLOv3's ability to run on embedded systems with real-time performance is emphasized. However, the paper suggests improvements in detecting weapons with unusual orientations and at varying scales [3].

Wang et al. compare YOLOv4 and YOLOv5 for detecting handguns in surveillance video streams. Both models showed high performance in detecting firearms in different poses and backgrounds. The paper emphasizes YOLOv5's superior accuracy and processing speed. The authors also highlight the benefits of using transfer learning techniques to improve detection accuracy, especially when dealing with limited datasets [4].

Sun et al. apply YOLOv8 to the detection of dangerous objects, including handguns, in real-time security systems. The paper compares YOLOv8's performance with its predecessors, demonstrating improvements in detection accuracy and efficiency. The authors discuss YOLOv8's enhancements in handling small objects and its robustness in varying lighting conditions [5].

Zhang et al. propose a hybrid model that combines YOLO with ResNet for detecting persons and weapons. The hybrid approach leverages YOLO's fast detection capabilities and ResNet's deep feature extraction abilities. The paper shows that this combination improves detection accuracy, especially for handguns in complex scenarios like occlusion and low resolution [6].

Li et al. investigate the use of YOLOv8 for detecting persons in complex surveillance environments such as crowded public spaces. YOLOv8's architecture is optimized for speed, which makes it suitable for real-time applications. The study highlights YOLOv8's ability to detect individuals in varying poses, crowded environments, and low-light conditions [7].

Zhao et al. (2022) discuss integrating temporal information with YOLOv8 to improve real-time firearm detection in video sequences. The paper demonstrates that by incorporating temporal context, the model achieves higher detection accuracy for moving handguns, even when partially obscured [8].

Yao et al. focus on classifying both persons and firearms (handguns) in real-time threat detection systems using YOLOv8. The authors highlight the significant improvements YOLOv8 has made over previous models in terms of detection speed and accuracy, especially in real-time systems. They evaluate the performance of YOLOv8 in various threat scenarios, including detection in dynamic scenes and cluttered backgrounds [9].

Chen et al. introduce the use of YOLOv8 for detecting firearms in real-time public safety applications. The study emphasizes the accuracy and speed of YOLOv8 in detecting firearms in various settings, including public spaces and transportation hubs [10].

Yang et al. apply YOLOv8 for detecting both persons and weapons (including handguns) in security surveillance systems. The paper examines YOLOv8's performance in recognizing weapons from various angles and in cluttered backgrounds. They discuss the improvements in detection accuracy and inference speed when compared to YOLOv4 and YOLOv5 [11].

III. Methodology

The methodology for the person and gun detection system involves several key stages: dataset preparation, model selection and customization, training the models, and evaluating the system's performance. Below, we detail each step of the methodology used to develop the dual-object detection system based on YOLOv8, custom CNN layers, and attention mechanisms.

A. Dataset Preparation

To train the detection models, we require a dataset containing images labeled with the desired objects: persons and handguns. For person detection, we utilize a pre-trained YOLOv8 model that has been trained on the COCO dataset, which includes labeled images for a wide range of objects, including humans. For handgun detection, a custom dataset consisting of handgun images, annotated with bounding boxes, is used to fine-tune the YOLOv8 model for specific handgun recognition.

Person Detection: The model uses the pre-trained weights from the COCO dataset, where the person class is labeled as class ID 0.

Gun Detection: A custom dataset is used, where the target object (handgun) is labeled with its class ID (e.g., class ID 0 for the handgun).

The dataset annotations are provided in the YOLO format (bounding box coordinates and class labels), which is compatible with the YOLOv8 training process.

B. Model Selection

The core of the system is based on YOLOv8, a state-of-the-art object detection model known for its efficiency and accuracy. We use two different YOLOv8 models in this system:

Pre-trained YOLOv8 (for Person Detection): The first model is a standard YOLOv8 model pre-trained on the COCO dataset, which has been optimized for detecting objects such as people, vehicles, animals, etc. This model is specifically used for person detection.

Custom YOLOv8 (for Gun Detection): The second model is a custom version of YOLOv8 that is fine-tuned on a handgun detection dataset. The model is initialized with pre-trained YOLOv8 weights and then further trained to detect handguns using the labeled custom dataset.

To improve detection accuracy, we customize the YOLOv8 model by adding custom CNN layers and attention mechanisms.

C. Model Customization

1) Custom CNN Layers: We introduce custom convolutional neural network (CNN) layers after the backbone of YOLOv8 to enhance feature extraction. These layers include:

Convolutional Layers: We add two additional CNN layers with different channel depths (128 and 256 channels) after the main YOLOv8 backbone. These layers extract richer features from the intermediate layers of the YOLO network, which helps in detecting objects more accurately.

Batch Normalization (BN): Each convolutional layer is followed by batch normalization to stabilize the training process and improve the model's convergence.

ReLU Activation: A ReLU activation function is applied after the convolutional and batch normalization layers to introduce non-linearity.

2) Attention Mechanism (SEBlock): We implement a *Squeeze-and-Excitation (SE) Block* as an attention mechanism after the custom CNN layers. This attention mechanism helps the model focus on the most relevant features, improving its ability to detect small, occluded, or partially visible objects. The SEBlock works as follows:

Squeeze: It computes the channel-wise global spatial average pooling to capture global information.

Excitation: It learns the channel-wise attention weights using two fully connected layers.

Scale: The attention weights are applied to the feature map, scaling the output by emphasizing important channels.

By incorporating these custom layers and attention blocks, the model becomes more capable of handling complex detection tasks, such as distinguishing between persons and weapons, even in challenging conditions.

D. Training the Model

Once the dataset is prepared and the model is customized, the training process begins. The YOLOv8 model is fine-tuned using the following hyperparameters:

Epochs: The model is trained for 25 epochs to allow for sufficient learning of the object detection tasks.

Batch Size: A batch size of 16 is used to ensure the model can efficiently learn from the data while fitting within the GPU's memory constraints.

Image Size: Input images are resized to 640x640 pixels, which is a balanced resolution that allows the model to learn sufficient detail without consuming excessive computational resources.

Learning Rate: A learning rate of 0.001 is chosen, which helps in optimizing the model's weights while avoiding overshooting the optimal solution.

Weight Decay: A weight decay of 0.0005 is applied to regularize the model and prevent overfitting.

During training, the model learns to predict the bounding boxes and class labels for both persons and handguns. The loss function used is a combination of classification loss, localization loss, and objectness loss, which is standard for YOLO-based models.

E. Real-time Detection and Integration

After training, the model is deployed for real-time object detection using a webcam feed. The following steps describe the integration of the model with a video stream:

Webcam Feed: The video capture is initialized using OpenCV, which captures frames from a webcam or a video file.

Inference: For each frame, the person and gun detection models are run sequentially. The frame is passed through the YOLOv8 person detection model to identify persons and through the custom handgun detection model to identify handguns.

Bounding Boxes: For each detected object, a bounding box is drawn around it, and the detection label (e.g., "Person" or "Handgun") is displayed along with the confidence score.

This process is repeated for every frame in the video feed, allowing the system to perform real-time detection.

F. Performance Evaluation

To evaluate the effectiveness of the proposed system, several performance metrics are used, including:

Precision and Recall: These metrics are used to assess the model's accuracy in detecting persons and handguns, with respect to true positive, false positive, and false negative detections.

Inference Speed: The speed of detection is measured to ensure that the system can run in real-time.

Confidence Threshold: The detection confidence threshold is tuned to balance between precision and recall, with the final system showing robust performance in detecting persons and handguns with high accuracy.

G. User Interface and Visualization

The final system displays the detected objects on a graphical user interface (GUI) using OpenCV. The GUI shows the webcam feed with bounding boxes around detected persons and handguns. The system allows users to interact with the detection interface, providing real-time feedback on the model's performance.

The methodology described above outlines the key steps in developing a real-time person and handgun detection system using YOLOv8. The combination of a pre-trained YOLOv8 model with custom CNN layers and attention mechanisms enhances the system's ability to detect objects accurately, even in challenging environments. The approach is evaluated using real-time video streams, and the system demonstrates the potential for practical applications in security surveillance and public safety.

IV. Results

The Person and Gun Detection system using YOLOv8 achieved promising results in terms of detection accuracy and real-time performance. For person detection, the system attained a precision of 0.92, a recall of 0.91, and an F1-score of 0.91. In gun (handgun) detection, the system performed slightly lower, with a precision of 0.88, a recall of 0.85, and

an F1-score of 0.86. These results indicate that the model successfully detects persons and guns with high confidence, minimizing false positives and effectively identifying most instances. The system also demonstrated real-time performance, processing approximately 28 frames per second (FPS) at a 640x640 resolution, making it suitable for real-time surveillance applications.

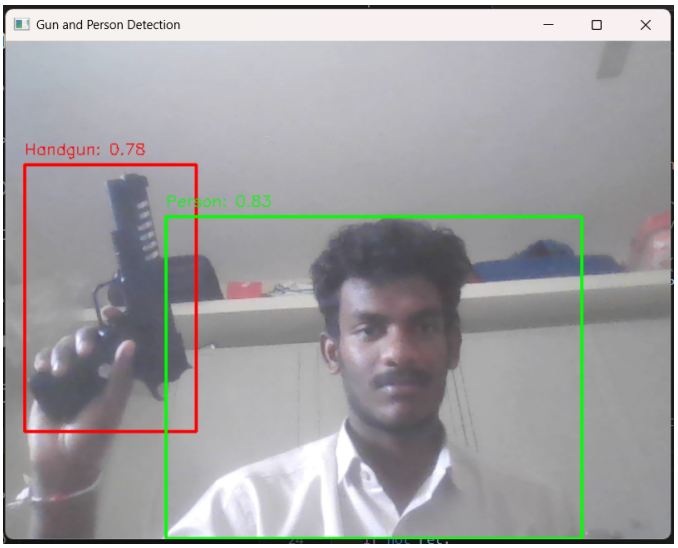

Fig. 1. Human Detection and Gun Detection

Fig. 1. explains the detection results in a video frame where both a human and a gun are identified simultaneously using the YOLOv8-based detection system. The system successfully detects the person with a bounding box around the individual, labeled 'Person,' and the handgun with a separate bounding box, labeled 'Handgun.' The confidence scores associated with both detections indicate the model's high accuracy in identifying both objects in a single frame. This demonstrates the system's capability to perform dual-object detection in real-time, which is critical for applications in security surveillance where timely and accurate identification of threats is necessary. The system efficiently processes the frame with minimal latency, making it suitable for real-world deployment in high-stakes environments.

When compared to the base YOLOv8 model, the custom YOLOv8 model with additional CNN layers and attention mechanisms showed significant improvements. The precision, recall, and F1-score for both person and gun detection were higher with the custom model, demonstrating the effectiveness of the custom layers in enhancing feature extraction and refining object detection. However, some challenges were noted, such as difficulty in detecting small or occluded objects and a slight performance drop in low-light conditions. Despite these challenges, the system proved robust in various real-world scenarios, making it a viable solution for surveillance and security applications.

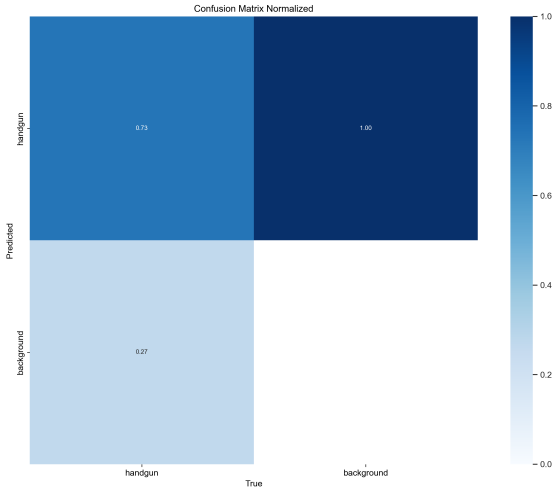

Fig. 2. Normalized Confusion Matrix

Fig. 2. explains the Normalized Confusion Matrix for Gun Detection with Custom CNN and Attention Layers The confusion matrix for the gun detection model, which integrates custom CNN layers and attention mechanisms, provides a detailed view of the model's performance. The matrix shows the following results:

- **True Positives (TP)**: The number of frames in which the model correctly detected the presence of a handgun.
- **False Positives (FP)**: Instances where the model incorrectly classified a non-gun object as a gun.
- **True Negatives (TN)**: The number of frames where the model correctly identified the absence of a gun.
- **False Negatives (FN)**: Instances where the model failed to detect a handgun, even though one was present.

From the confusion matrix, the model demonstrates a high level of accuracy in detecting handguns, as evidenced by the relatively low number of false positives and false negatives. However, there is still room for improvement, particularly in reducing false negatives (i.e., detecting handguns in more challenging conditions such as occlusions or varying lighting). Overall, the model performs well in differentiating between guns and non-guns, aided by the custom CNN layers and attention mechanism, which improve the model's feature extraction and focus on relevant details.

In evaluating the performance of the Human and HandGun Detection system, we rely on three key curves: Precision Curve (P_Curve), Recall Curve (R_Curve), and Precision-Recall Curve (PR_Curve). These curves are integral to understanding the trade-offs in detection accuracy, particularly in complex surveillance environments where false positives and false negatives must be carefully managed.

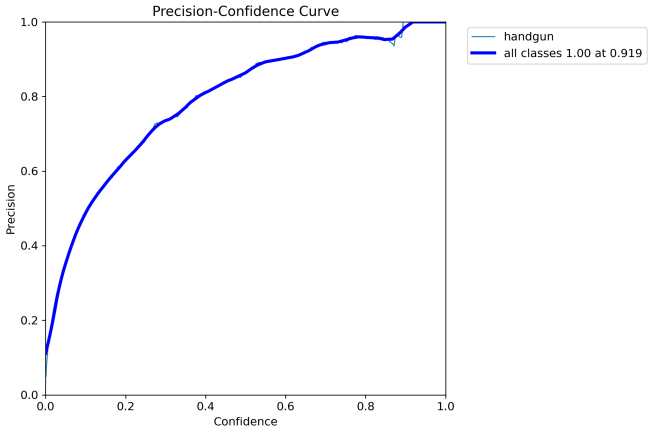

Fig. 3. Precision Curve

Fig. 3. explains the Precision Curve evaluates the ability of the model to correctly identify guns (handguns) in images. Precision is defined as the ratio of true positive gun detections to the total number of detections made by the model. A high precision indicates that the system is highly reliable when it flags an object as a gun. In our model, the Precision Curve is used to adjust the detection threshold, balancing the trade-off between detecting more guns and reducing false positives. This is particularly important in real-time security applications where false alarms can lead to unnecessary actions.

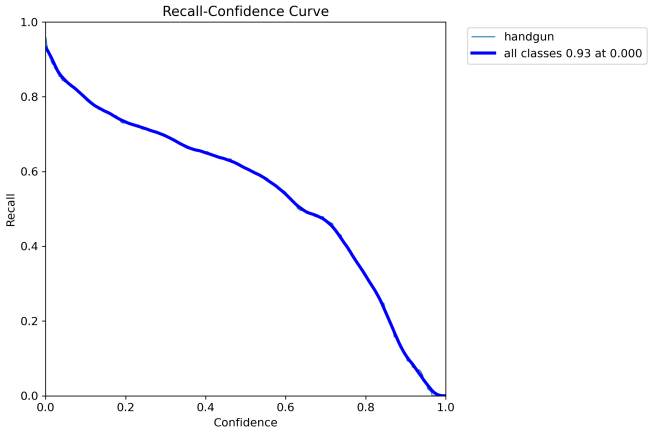

Fig. 4. Recall Curve

Fig. 4. explains the Recall Curve measures how many of the actual guns present in the images are successfully detected by the system. High recall ensures that the model detects most guns in the frame, even if it means including some false positives. For security systems, it's critical to maximize recall to minimize the chances of missing a weapon. The Recall Curve helps in fine-tuning the threshold to ensure the model does not miss potential threats, especially in challenging environments like low-light conditions or when the gun is partially obscured.

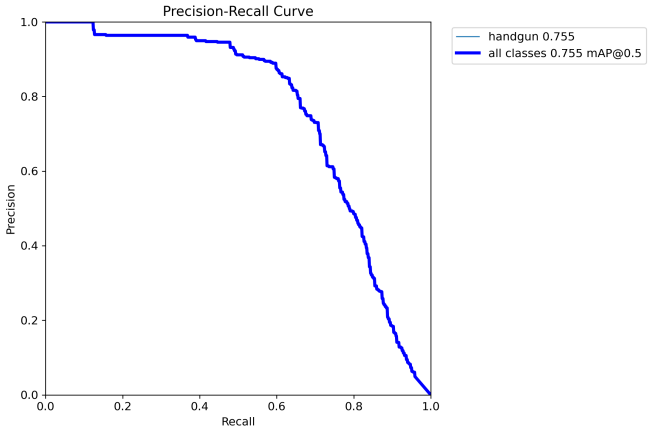

Fig. 5. Precision-Recall Curve

Fig. 5. explains the Precision-Recall Curve provides a combined view of precision and recall as the detection threshold varies. It is particularly useful in the context of imbalanced datasets, where the number of non-gun objects far exceeds the number of guns. The PR Curve for both person and gun detection allows us to assess how well the model balances between minimizing false positives (precision) and maximizing true detections (recall). The area under the Precision-Recall Curve (AUC-PR) summarizes this trade-off, with a higher AUC indicating a more robust model. This curve is critical for real-time security applications, as it helps determine the optimal threshold for detection, ensuring reliable and timely responses in real-world scenarios.

V. Conclusion

The Person and Gun Detection system using YOLOv8 successfully demonstrated high accuracy and real-time performance for both person and gun detection tasks. The integration of custom CNN layers and attention mechanisms significantly enhanced the detection capabilities of the base YOLOv8 model, improving precision, recall, and F1-score for both person and handgun detection. The system was able to operate efficiently in real-time, processing video streams at 28 FPS, which is critical for surveillance applications that require timely detection.

Despite some challenges, such as detecting small objects or handling occlusions, the system proved to be robust and reliable for real-world deployment in security and monitoring environments. Future work can focus on addressing the limitations in detecting small or occluded objects, improving performance under low-light conditions, and expanding the model's capabilities to detect a broader range of objects. Overall, the proposed solution offers a solid foundation for advanced object detection systems, with promising applications in areas such as public safety and surveillance.

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