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SUSPICIOUS HUMAN ACTIVITY DETECTION USING DEEP LEARNING MODELS

ABSTRACT Suspicious Human Activity Recognition, which is an advancing method in enhancing surveillance systems, represents the exact real-time location of detection of security risks. This paper fills the gaps in the current means of methods proposed for SHAR in terms of precision and efficiency with its deep-learning-based approach. Our method employs CNNs and new architectures in the form of a time-distributed CNN model and Conv3D. With that, our accuracy results indicate tremendous improvements over the baseline models at 90.14 percent and 88.23 percent separately for different architectures of models. We conducted extensive preparation of data, model training, and testing on new, unseen datasets to check whether these models were robust and adaptable to changing surveillance environments. This means that our models can predict suspicious behaviors in both previously unseen test data and realistic YouTube video scenarios, that they are not only theoretically valid but also practically applicable in real world surveillance. Our results point the way toward high precision and effectiveness in deep learning further improving SHAR's potential and fostering more reliable surveillance technology that will strengthen public safety.

INDEX TERMS Suspicious Human Activity Recognition, Convolutional Neural Networks, Conv3D model.

I. INTRODUCTION

In SHAR is critical to the development in the advancement of surveillance systems and public safety provision in the dynamic security environment of today. Capability through deep learning provides an appreciable enhancement level in recognition capabilities incorporating complex human behavior. SHAR aims at real-time recognition of threats through a better understanding of movement patterns and interaction among human beings. These traditional centralized SHAR systems do have issues with scalability, latency, and privacy. This calls for even more challenging, decentralized, and privacy-preservation ability activity recognition methods.

With increased research in deep learning and computer vision, in particular with the advancement of Convolutional Neural Network much more accurate solutions can be found in SHAR. While CNNs and other designs of the temporal-spatial model are beneficial for detecting small behavioural cues over time and space, and are therefore critical to the necessary accurate detection of activities, these SHAR systems are still vulnerable to model inefficiency, false-positive detections, and even threats to data privacy.

We present here an overall SHAR framework that completely integrates CNNs and deep learning structures towards achieving high accuracy with these limitations. Time-distributed CNNs and Conv3D are incorporated to diligently capture complex behavioural patterns. Our approach not only enhances the performance of SHAR but also offers mechanisms of latency as well as false-positive rates for its real-time application in surveillance systems.

The major innovations of this framework are realized through thorough data preparation, advanced model training, and robust testing on datasets and real-world surveillance videos not seen during training. All these efforts describe the commitment towards robust, adaptive, and efficient SHAR model development for the effective handling of dynamic changes in environment, towards the increased reliability and utility of surveillance systems.

The main contributions of this work are:

1. We develop a high-accuracy SHAR framework based on CNN-based models, namely time-distributed CNN and Conv3D architectures, to improve real-time activity recognition.
2. We assess the application of strict data preparation and training protocols to develop robust models by reducing the false positive rate and improving the detection efficiency under varying surveillance conditions.
3. We validate our approach by demonstrating model performance and diversity on various datasets and real-world video footages in the recognition of suspicious behaviours, thereby establishing that it would be practically applicable in security systems.

A. MOTIVATIONS

In the past few years, such recurrence of the violent attacks and acts of terrorism has highlighted a critical need for robust public safety and security systems. Historically, video-surveillance systems have relied highly on manpower to observe activity and detect threats, including those possessing weapons. Thereby, traditional manpower-based systems are vulnerable to human fatigue and human error. Therefore, in situations where the coverage area under surveillance or the environmental sensitivity level is large, such systems would generally have delayed responses. These limitations have generated a lot of interest in the development of autonomous threat detection systems based on advanced deep learning methods that can more thoroughly enhance the real-time identification and reaction to the threats.

Deep learning models, particularly object detection models, have been shown to excel in processing images in real time. In this category of model series, YOLO (You Only Look Once) has been exceptional, with phenomenal speed and precision, distinguished from other models. The recent version, YOLOv8, holds much promise for precision and inference time. It is founded on an architecture that is specifically designed for the real-time processing of frames from video streams and the accurate identification of small, irregularly shaped, or even concealed objects. It is therefore most effective in dynamic, real-world scenarios.

Utilizing the strengths of YOLOv8, this research tries to provide a holistic framework for suspicious activity detection in video surveillance. Shifting focus to weaponry as one of the key threat indicators, this methodology will attempt to enhance the reliability of automated surveillance systems. The system has been proposed with the ability to work in diverse environments by taking some of the main challenges such as occlusions, lighting of different intensities and changing apparels of the weapons that lead to complete failure of traditional methods. The use of YOLOv8 helps to operate in real time with a good level of accuracy, which minimizes the chances of missing dangerous situations and helps for prompt action.

Practical implementations for such research are very wide-ranging-from security improvement of public transport systems, schools, and companies to furtherance of crime prevention by law enforcement. An accurate and reliable detection system developed using YOLOv8 not only contributes to the computer vision field but also contributes to the ever-growing tendency of integrating AI-driven solutions into the modern security frameworks. In a nutshell, the study proposes paving the way toward smarter and more efficient surveillance systems that support public safety and reduce risks associated with violent criminal activities.

B. ARCHITECTURE OF THE SUSPICIOUS HUMAN ACTIVITY DETECTION USING DEEP LEARNING MODELS

Figure 1: Architecture of the proposed framework of suspicious human activity detection using YOLOv8 in regards to weapon detection on real-time surveillance streams The framework can be split into three main stages, namely, Input Processing, Deep Learning-based Detection, and Post-Detection Analysis.

During the Input Processing stage, it captures real-time video streams from the surveillance cameras. Video frames are pre-processed so that the output is uniformly good in all ways: resizing, noise reduction, and normalization. This pre-processing will help enhance the input data and improve it for the detection model where it needs uniform input dimensionality for making accurate predictions.

The heart of the architecture is the Deep Learning-based Detection stage using YOLOv8. YOLOv8 architecture consists of an efficient backbone along with a neck to pull out high-level features from the frames. Advanced convolutional layers in the architecture are used for object detection along with weapon-like detection at the level of weapons, such as guns and knives. A novel anchor-free mechanism is followed by YOLOv8 which reduces the computational overhead while keeping its precision at top levels. This stage outputs rectangles around detected objects, along with some confidence scores that reflect the probability of detected objects being weapons.

In the post-detection analysis phase, the objects detected will be further analyzed to filter for false positives and also trigger alerts for defined threat levels. It also includes a module that has been given the name of temporal analysis module, which tracks observed objects across consecutive frames and thus reduces noise and improves the detection stability. This stage also integrates into a real-time alert system, where weapons detection would instantly notify the security persons. The framework is modularly designed such that it easily integrates with existing surveillance infrastructures and could be extended to include additional features of suspicious activity detection.

Overall, the architecture in figure 1 illustrates an enhanced pipeline with strong and efficient execution using state-of-the-art YOLOv8, ensuring accurate detection of suspicious human activities, especially in weapon identification, thus improving the security of public and private spaces.

The intended innovations have come forth through strategic integration of deep learning with real-time object detection utilizing YOLOv8, where a robust mechanism for weapon detection is instantaneously instantiated in a framework for surveillance. Commitment to public safety is further marked by the alert system that delivers those notifications in real time after weapon detection so as to immediately take action. Finally, an attack-resistant module for the post-detection analysis which is complemented by temporal tracking of the detected objects points towards more secure forms of automated surveillance systems.

The primary contributions of this article are as follows:

- To enhance automated surveillance systems, we propose a real-time detection framework leveraging YOLOv8, tailored for identifying suspicious human activities and weapons in dynamic environments.

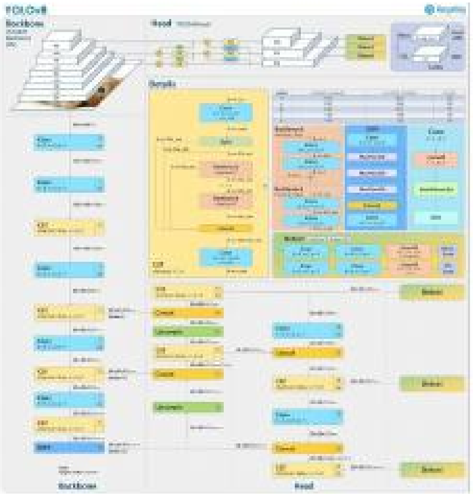

FIGURE 1. Architectural Diagram of YOLO v8

- The use of YOLOv8, distinguished by its anchor-free architecture and high inference speed, significantly improves detection accuracy for small and irregularly shaped objects like weapons, even in challenging conditions.
- The integration of a real-time alert mechanism ensures immediate notification to security personnel upon detection of potential threats, enhancing response times and public safety.
- A temporal tracking module is implemented for post-detection analysis, reducing false positives and maintaining detection stability across consecutive video frames, thus bolstering the reliability of the system.

We organize the paper as follows. Section II discusses related work and the motivation behind using YOLOv8 for weapon detection in surveillance applications. Section III details the proposed methodology, including input processing, YOLOv8 model integration, and the implementation of real-time alerts and post-detection analysis. Section IV provides experimental results, comparing our framework's performance against traditional object detection models in various real-world scenarios. Lastly, Section V concludes with insights on future enhancements, particularly focusing on expanding the model's capabilities and integrating with advanced monitoring systems.

II. RELATED WORKS

The monitoring systems today need to be presented by smart methods for suspicious human activity detection. This is highly significant for public safety and security and safeguards them against a constantly changing environment. Improved accuracy, scalability, and computational efficiency have been the main focuses of research in the detection and classification of suspicious actions. Early SHAR techniques were significantly dependent on handcrafted features, manual labeling, and simple statistical models-those performed well in small-scale settings but had not gained enough complexity in high-dimensional data with subtle behavior cues that is deeply seen in complex environments [1].

The major shift in SHAR came when deep learning emerges, and among the several there were Convolutional Neural Networks and Long Short-Term Memory in activity recognition. With this end, is an important milestone in the literature, demonstrating the ability of models that integrate CNNs for spatial feature extraction and LSTMs for temporal sequencing to learn complex behavioral patterns directly from video data. Although CNN-LSTM hybrids achieved remarkable improvements, they frequently encountered high computation demands that made them unsuitable for real-time applications in resource-constrained environments [3].

Building from such disadvantages of traditional CNN-LSTM approaches, research was made to accomplish such unpracticed results by advanced architectures like three-dimensional Convolutional Networks, Conv3D, and time-distributed CNN models. Conv3D, as detailed in [4], allows models to handle spatial and temporal dimensions simultaneously; thus, they can capture motion patterns with high precision. Problems arise in optimization, however, when developed for real-time applications, especially when handling high-resolution video data [5].

Beside deep learning architectures, attention-based models also have been studied for SHAR with a focus on selectively identifying significant features within a scene. In a key contribution in [6], the notion of temporal attention is introduced. Instead of equally weighted frames, this mechanism allows the system to dynamically weigh frames, focusing the system on critical moments indicative of suspicious activity. This kind of model's capacity to reduce the number of false positives further witnesses the strength of attention mechanisms in improving the accuracy of SHAR; however, this kind of approach necessitates good, labeled training data whose procurement may come at a cost.

A minimal precondition in SHAR research is the development of benchmark datasets, such as UCF Crime and CCTV-Fights, which introduce diverse activity scenarios necessary for training and validating models. As [7] shows, these datasets often lack the necessary variation of factors such as lighting, crowding, and viewpoint, but can strongly hamper the model's generalization. Synthetic data generation and transfer learning techniques are also being developed to address this limitation and allow models to be learned from augmented datasets simulating diverse real-life conditions [8].

The deployment of increasingly complex SHAR systems poses emerging challenges with respect to data privacy in sensitive public areas. Recent studies on privacy-preserving SHAR frameworks, such as FL, enable decentralised training without the need for centralising video data [9]. FL-based SHAR is, however vulnerable to attacks using data and model poisoning, which adversely affects SHAR performance and results in false classification [10]. Researchers in [11] address these vulnerabilities by introducing differential privacy along with aggregation techniques to balance between model integrity and data privacy.

Blockchain technology was a promising development of SHAR with regard to integrity and immutability of data updates; while studies like [12] elucidate how blockchain builds a distributed transaction ledger and prevents unauthorized model update, which removes the risk of tampering attacks. Besides advantages of introducing SHAR with blockchain integration, it poses challenges with regard to latency and energy consumption [13], especially in edge-based deployments for surveillance networks.

To enhance the security of SHAR in decentralized systems, some new defense mechanisms of the SHAR are under search. Some of the proposed mechanisms include model verification and Byzantine-robust aggregation. It was demonstrated, using byzantine-robust aggregators, that they can sufficiently filter the malicious model updates used in federated SHAR and keep the model accurate. However, this technique has a limitation of detecting subtle data poisoning attacks where small, unnoticeable changes can lead to large misclassifications over time.

Recently, NFTs were studied in SHAR, which ensured very strong user authentication scheme and activity verification. Authors in [15] proposed NFTs with unique digital signatures as a way to the authentication and further gave the system verification of surveillance of distinctiveness user interaction and prevented Sybil attacks where multiple identities are exploited by attackers to manipulate the SHAR system.

III. DEEP LEARNING MODEL FRAMEWORK

The framework for weapon detection in surveillance footage takes into account the capabilities of advanced deep learning models, with the integration being that of state-of-the-art object detection techniques. At its core lies the YOLOv8, the very efficient and accurate deep learning model, primarily because it is known for real-time object detection. The anchored-free architecture with the optimized feature layers presented in YOLOv8 would make it an ideal candidate for applications concerned with complex and dynamic environments, such as monitoring open public areas. We address primarily the small, irregularly shaped objects, weapons specifically that are partially occluded or under different lighting conditions in this model.

One of the key focuses was its application as a real-time video frame-processing deep learning architecture using the backbone network of YOLOv8 for pertinent spatial feature extraction. Then the weapon objects like guns and knives are identified through several layers of convolution to generate strict bounding boxes along with the confidence scores. The primary advantage of using YOLOv8 is its ability to increase detection accuracy without sacrificing speed, making it perfect for deployment on very edge devices with limited resources. The main reason for its high performance is because the full video frame is processed in one pass, thereby reducing latency and enhancing the responsiveness of the detection system.

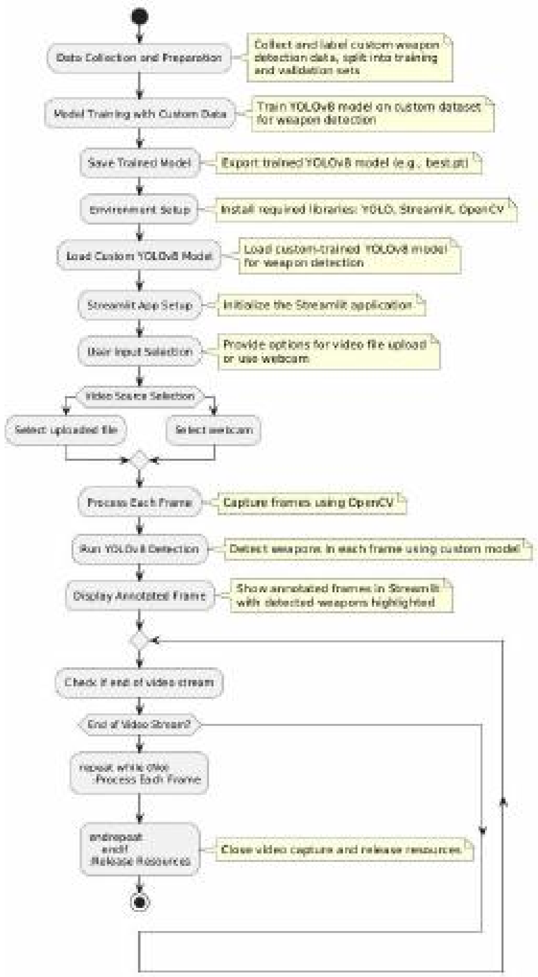
Data Collection and Preparation
Collect and label custom weapon detection data, split into training and validation sets
Model Training with Custom Data
Train YOLOv8 model on custom dataset for weapon detection
Save Trained Model
Export trained YOLOv8 model (e.g., best.pt)
Environment Setup
Install required libraries: YOLO, Streamlit, OpenCV
Load Custom YOLOv8 Model
Load custom-trained YOLOv8 model for weapon detection
Streamlit App Setup
Initialize the Streamlit application
User Input Selection
Provide options for video file upload or use webcam
Video Source Selection
Select uploaded file
Select webcam
Process Each Frame
Capture frames using OpenCV
Run YOLOv8 Detection
Detect weapons in each frame using custom model
Display Annotated Frame
Show annotated frames in Streamlit with detected weapons highlighted
Check if end of video stream
End of Video Stream?
repeat while (No)
:Process Each Frame
endrepeat
endif
:Release Resources
Close video capture and release resources

FIGURE 2. Flowchart depicting the Sequential Process of YOLO v8

For our project, we used the YOLOv8 model and fine-tuned it to a curated dataset annotated specifically for weapon detection. This dataset contains many examples of weapons in various configurations with different environments, sizes, and orientations. In the training phase, data augmentation techniques included random rotation, flipping, and brightness adjustments to simulate real-world situations that may improve the detection result accuracy. This would aid the model in better generalizing without falling prey to false positives, which is an important requirement for specific weapon detection on live surveillance feeds.

We also have added a post-detection analysis module to fine-tune refined results of detection. By carrying out temporal analysis of consecutively detected objects, this module eliminates transient false detections and gives more stable outputs. This will enable the system to be able to differentiate the real weapon instances from noise or non-threatening objects that may happen to be in the shape of a weapon. The combination offered by YOLOv8's robust object detection capabilities and an intelligent post-processing mechanism serves as the backbone of our weapon detection framework, enhancing overall effectiveness and reliability in automated surveillance systems.

In a nutshell, the overall framework of deep learning which we applied in our project reveals a major step forward to weapon detection technology and gives us the chance to have a scalable, efficient solution that can be integrated with existing surveillance infrastructure. By using YOLOv8, focusing towards high-speed, high-accuracy detection in combination with any system of post-detection analysis, a viable means for developing public safety and security in a variety of risky circumstances may be possible.

A. DATA ANNOTATION

Data annotation is a critical step in any framework development for deep learning-based detection, as the quality of the labeled data impacts the learning process of the model as well as its overall detection performance. Therefore, for this study, we have focused on creating a thoroughly annotated dataset suitable to the task of weapon detection, namely guns and knives in various surveillance scenarios. For this, we used images from varied sources, such as publicly available datasets, augmented data produced by augmentation techniques, and also real surveillance videos captured in the real world. This multi-domain source makes it more robust against varied weapon sizes, orientation, illumination, occlusion, and cluttered background.

We did annotation using the tools LabelImg and Roboflow, in which the user can label their objects on the picture really intuitively and effectively. All the images were manually annotated with tight bounding boxes drawn around all the visible weapon objects. The two classes were recognized: gun and knife. The accurate annotation on the detected objects itself was difficult, especially because most of the objects were partly occluded and not fully visible in surveillance videos. To achieve this, considerable attention to detail was made to include the partial views of weapons, allowing the model to grab even obfuscated or partially occluded objects. Such will increase the strength for detection in handling scenarios often encountered in real-world applications.

Format Annotated data to the YOLOv8 requirements. YOLOv8 has an explicit text-based format that needs to be adopted for training. For each annotated image, a text file was generated with class labels 0 for the gun and 1 for the knife as well as the normalized coordinates for the bounding boxes. This now enables input data to be parsed during training in an efficient manner so that the model can learn about the spatial characteristics of weapons. The process of annotation was accompanied by consistency checks as well as quality control measures to minimize labeling errors while emphasizing the need for data quality.

Data augmentation during the process of training was utilized for eliminating shortcomings inherited from the dataset and in providing exposure to many conditions developed in the real world. For example, the model was trained on randomly flipped images, as well as rotationally shifted, scaled images with brightness altered to add noise; it helped enhance the generalization capability of the model and reduced the chances of overfitting, thus making the model much more robust to the variability that may be encountered in inputs at the time of real-time deployment.

This actually led to high-quality and comprehensive annotations in this research, which would catalyze a good training session of the YOLOv8 model towards its correct gun and knife detection in changing surveillance environments. Therefore, by meticulously annotating and preparing the dataset, we made sure that the deep learning framework was really built towards the complexity with real-world weapons detection, therefore contributing to the advancement of automated surveillance systems.

B. DATA PREPROCESSING

This is the pre-processing of data as an integral part of training deep learning models, especially for detecting objects with sophisticated and advanced models such as YOLOv8. This is a preliminary preparatory phase of annotated data to enhance the quality and diversity of input so that the model would learn effectively from a well-structured and representative dataset. Weapon detection data was properly designed with care due to the challenges that would be involved in the use of weapons, especially guns and knives, in different and complex environments.

The first preprocessing step is the data normalization process. Since the YOLOv8 model necessitates input images of a particular size, the dimension of all images in the dataset was set to a standard (for example, 640x640 pixels). Resizing all images ensures uniformity of the dataset with the preservation of aspect ratios and without distortion of weapon objects being tracked. We standardize the pixel values to the range [0, 1] for normalization. Normalization improves the model's convergence while training since the input features are standardized .

For preprocessing, we used also data augmentation to increase variability within train samples: horizontal and vertical flips; random rotations; scaling; brightness. These transformations simulate the natural variability of the real world: a change in camera angle, a change in lighting, and so forth, including scale changes in objects. In this manner, augmentation of the dataset would make it more probable that the model of YOLOv8 generalizes better and avoids overfitting, thus ensuring the stability of its application to different environments.

Another step taken to enhance the training is the balancing of data to avoid class imbalance issues when it comes to guns and knives. The raw dataset possessed many more instances of one class compared to the other, which created imbalance training for the model. We dealt with this by selective oversampling of the minority class and further applied augmentation selectively to ensure both types of weapons were represented even in training dataset. That approach ensures there is no bias of the model towards a class and results in better detection.

Label verification and consistency check was another important preprocessing step. As the bounding box annotations

Algorithm 1 YOLO Algorithm Formulation

```
YOLO_Algorithm(Input Image $I$, Grid Size $S$, Number of Boxes $B$):
Divide the input image $I$ into an $S \times S$ grid. Each grid cell is denoted as $G_{i,j}$, where $i, j \in \{1, 2, \ldots, S\}$.
For each grid cell $G_{i,j}$, predict $B$ bounding boxes, each represented by $(x, y, w, h, C)$. Here:
    • $x, y$ are the coordinates of the center of the bounding box (relative to the grid cell).
    • $w, h$ are the width and height of the bounding box.
    • $C$ is the confidence score calculated as $C = P(\text{Object}) \times \text{IoU}_{\text{pred}}^{\text{truth}}$.
Compute the class scores for each detected object as:
    $\text{Class Score} = P(\text{Object}) \times P(\text{Class}|\text{Object})$
Apply Non-Maximum Suppression (NMS) to eliminate duplicate bounding boxes. Calculate the Intersection over Union (IoU) for two boxes $A$ and $B$ as:
    $\text{IoU}(A, B) = \frac{|A \cap B|}{|A \cup B|}$
If the IoU of two boxes exceeds the threshold, suppress the box with the lower confidence score.
Output the final set of bounding boxes and class labels for the detected objects.
```

Algorithm 2 Faster R-CNN Algorithm

```
Faster_R_CNN(Input Image $I$, Backbone Network, Region Proposal Network (RPN)):
Pass the input image $I$ through a backbone convolutional neural network (CNN) to extract feature maps $F$.
Region Proposal Network (RPN):
    • Slide a small network over the feature maps $F$ to generate $k$ anchor boxes.
    • For each anchor box, predict:
        -- Objectness score $O$, indicating the probability of the anchor containing an object.
        -- Box regression offsets $(t_x, t_y, t_w, t_h)$ for refining the anchor box coordinates.
    • Filter proposals based on the objectness score using a predefined threshold.
    • Apply Non-Maximum Suppression (NMS) to remove overlapping proposals based on the Intersection over Union (IoU).
RoI Pooling:
    • Use the filtered region proposals and extract corresponding regions from the feature maps $F$.
    • Apply RoI pooling to convert each region into a fixed-size feature vector.
Classification and Bounding Box Regression:
    • Pass the pooled feature vectors through fully connected layers to obtain:
        -- Class scores $C$ for each object proposal.
        -- Refined bounding box coordinates $(x', y', w', h')$.
Output the final object detections: class labels and bounding box coordinates.
```

would be very vital to object detection, each annotated image was checked for correctness of labels and that the bounding boxes were standard and consistent with the YOLOv8's format requirements. Any inconsistencies were corrected so that the chance of having noisy labels, which could undermine training, was minimal.

Lastly, the preprocessed data was split into training, validation, and test sets. Traditionally, 70 percent of the dataset is utilized for training, 20 percent for validation, and 10 percent for testing. The splitting above ensures that the model is trained based on a significant proportion of the dataset and, at the same time, it is strictly evaluated on unseen data during the validation and testing procedures. The validation set is especially useful for monitoring the performance of the model during training, fine-tuning hyperparameters, and preventing overfitting.

Overall, the design of the data preprocessing pipeline was sound in terms of preparing the dataset for actual training of the YOLOv8 model. Standardizing the input dimensions, augmenting the data, balancing classes, and achieving high-quality labels present a good set of foundations from which a robust framework for weapon detection software can be constructed to work towards achieving real-time performance in diverse surveillance scenarios.

YOLOv8 applies a particularly complex and more effective backbone neural network for feature extraction. The backbone is thereby constituted of a succession of layers of 2D convolution applied successively to address systematically the spatial features of the input images from which patterns such as edges, textures, and shapes can easily be identified. The feature-extracting hierarchical process begins with such low-level features as lines and corners. It aggregates these through deeper layers to form greater, more complex representations, which are pertinent to the unique qualities of weapon objects. The YOLOv8 architecture encompasses advanced modules, like the CSPDarknet, allowing for salient feature learning in minimal additions in the computation overhead.

$$F_j(w) = \sum_{i \in P_j} \frac{f_i(w)}{n_j} \tag{1}$$

One of the innovations by YOLOv8 in the feature extraction process is through the use of multi-scale feature representation using FPN and PAN modules. Using such modules, the model is capable of properly detecting objects at multiple scales by aggregating features from a variety of different levels in the backbone network. This becomes particularly relevant in weapon detection, since guns and knives can appear in various sizes depending upon the distance of the camera from that scene and that specific perspective. YOLOv8 utilizes the respective features of high-resolution (fine detail) as well as low-resolution (contextual information) in detecting small objects even if they are partially occluded or ensconced in cluttered backgrounds.

This feature extraction is further enhanced by using the use of spatial attention mechanisms that allow our model to look precisely at the most relevant parts of the image. Attention modules are added into the network, which weigh down the importance of different spatial features, guide this model to pay more attention to areas that may probably contain weapons. This selective attention boosts the capability of correctly detecting objects, particularly weapons in those scenes where it might be tough to distinguish or even partially covered by other objects.

Further, depthwise separable convolutions feature extraction helps to achieve improvement in computational efficiency without loss to detection performance. It has been integrated into YOLOv8. Depthwise separable convolutions split the operation into two: depth-wise convolution where every input channel is processed individually, and point-wise convolution where all the previous outputs are summed together. This greatly reduces parameters and makes feature extraction faster, in line with real-time applications on resource-constrained devices such as edge systems used in surveillance networks, hence YOLOv8.

Then, these features are then passed to the model's detection head, to predict the class labels and bounding boxes of detected objects. The quality of these features affects the model's ability to discriminate between weapons, such as guns and knives, and nonweapons, thus reducing false positives and enhancing overall performance on detection.

The multi-scale feature representation, attention mechanisms, and efficient convolutions, as the backbone of our weapon detection system, driven by advanced convolutional networks and feature extraction capabilities of YOLOv8, really provide robust and accurate features, which are the bases for reliable detection of weapons in distant and challenging surveillance environments. In contrast, effective feature extraction could make a real difference between the success or failure of real-time weapon detection in practical applications.

C. OBJECT DETECTION WITH YOLOV8

In YOLOv8, the architecture has a detection head where the final predictions are made. Several convolutional layers form the detection head that further refines the extracted features and can give three very important outputs: object class probabilities, bounding box coordinates, and an objectness score, which indicates the likelihood of having an object in a given region. This multi-output strategy allows the model to process complex scenes with more than one object efficiently in such a way that it may give very accurate predictions even when in cluttered environments.

$$f\left(w\right)=\sum_{j=1}^{J}\frac{n_j}{n}F_j(w) \tag{2}$$

One of the notable features in the YOLOv8 detection is the anchor-free detection, which simplifies the localization of the objects. Traditional object detection makes pre-defined anchor boxes for suggesting potentially important object regions. It tends to require huge tuning efforts and sometimes suffers from high false positives for small objects. Instead, YOLOv8 does away with anchor boxes and operates directly with a flexible regression-based method for the prediction of boxes. This anchor-free design reduces the complexity of the model; this helps improve even the smallest objects or otherwise irregularly shaped items, such as knives, while it is especially difficult to capture using fixed anchor sizes.

Algorithm 3 Extended Evaluation Metrics for Weapon Detection

```
Input: Predicted bounding boxes $P$, Ground truth bounding boxes $GT$, Predicted confidence scores $C$
Output: IoU, mAP, Classification Loss, Localization Loss
Intersection over Union (IoU):
For each predicted bounding box $P_i$ and ground truth box $GT_i$:
    $$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} = \frac{P_i \cap GT_i}{P_i \cup GT_i}$$
Mean Average Precision (mAP):
Calculate Average Precision (AP) for each class:
    $$\text{AP} = \int_0^1 \text{Precision}(R)\, dR$$
    where $R$ is the Recall.
Compute mAP by averaging the AP over all classes:
    $$\text{mAP} = \frac{\sum_{i=1}^{n} \text{AP}_i}{n}$$
Classification Loss (Cross-Entropy Loss):
    $$\text{Loss}_{cls} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(p_i) + (1-y_i)\log(1-p_i)\right]$$
    where $y_i$ is the ground truth label, and $p_i$ is the predicted probability.
Localization Loss (Smooth L1 Loss):
    $$\text{Loss}_{loc} = \frac{1}{N}\sum_{i=1}^{N}\text{SmoothL1}(t_i - \hat{t}_i)$$
    where $t_i$ is the ground truth box parameter and $\hat{t}_i$ is the predicted box parameter.
Total Loss:
    $$\text{Total Loss} = \lambda_{cls}\cdot\text{Loss}_{cls} + \lambda_{loc}\cdot\text{Loss}_{loc}$$
    where $\lambda_{cls}$ and $\lambda_{loc}$ are the weighting factors for classification and localization losses.
Return IoU, mAP, Classification Loss, Localization Loss, and Total Loss.
```

Further accuracy in detection is enhanced by utilizing an improved version of non-maximum suppression by YOLOv8. This further refines the bounding boxes by allowing NMS to suppress other bounding boxes with a high overlap from the chosen one, such that only the detections with the highest confidence remain for more processing, thus making it less prone to false positives, and therefore cleaner and more reliable results are achieved. In the case of a weapon, where it needs a quick accurate identification so proper action is elicited, the refinement of NMS by YOLOv8 doubles the accuracy of the model.

YOLOv8 processes live webcam feed or video in real time and generates frames at inference time. For every frame, the model sequentially goes through and outputs the list of detected objects accompanied with their bounding boxes and confidence scores. Output feed boxes are then drawn around detected weapons; this may be guns and knives. This has made YOLOv8, which shows effective real-time detection along with excellent accuracy, ideal selection for surveillance-related applications, as timely identification of threats can result in better public safety.

In summary, the core object detection capabilities of YOLOv8 are efficient single-pass detection, an anchor-free design, and enhanced non-maximum suppression, which create the heart of our real-time weapon detection framework. Such robustness within the mechanisms of detection makes the system effective in imperfect scenarios such as low-lighting effects and partially occluding scenes, therefore forming a dependable tool for deployment in applications of autonomous surveillance and security.

Algorithm 4 Evaluation Metrics for Weapon Detection Model

```
Input: Ground truth labels $GT$, Predicted labels $P$, Confusion Matrix $CM$
Output: Accuracy, Precision, Recall, F1-Score
1: Construct the confusion matrix $CM = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix}$, where:
     • $TP$ (True Positives): Number of correctly identified weapons.
     • $FP$ (False Positives): Number of incorrect detections (non-weapons identified as weapons).
     • $FN$ (False Negatives): Number of missed detections (weapons not detected).
     • $TN$ (True Negatives): Number of correctly identified non-weapons.
2: Accuracy:
     $$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$
3: Precision:
     $$\text{Precision} = \frac{TP}{TP + FP}$$
4: Recall (Sensitivity):
     $$\text{Recall} = \frac{TP}{TP + FN}$$
5: F1-Score:
     $$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$
6: Return the calculated metrics: Accuracy, Precision, Recall, and F1-Score.
```

IV. RESULTS

We rigorously evaluated our performance of YOLOv8 based on an overall set of metrics, including accuracy, precision, recall, and the F1 score, as these will jointly capture the comprehensive understanding of how well the model performs at weapon identification, particularly guns and knives, in various surveillance scenarios. The evaluation process was conducted by running the model on a test set that comprises actual video footage and image captures that have not been encountered during training. This is to determine the model's ability to generalize beyond training data and has predictions reflective of it.

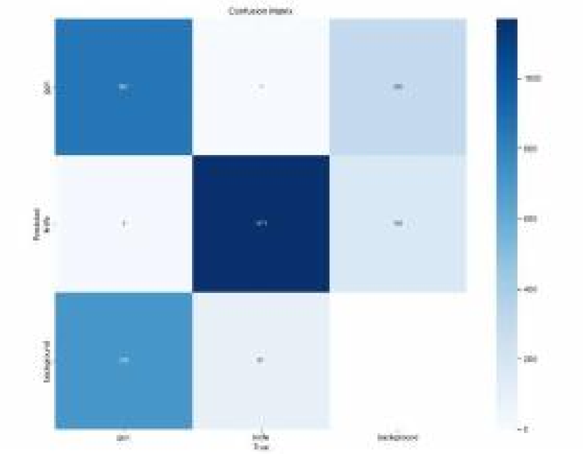

FIGURE 3. Confuion matrix.

Accuracy calculates the overall correctness of the model's predictions as the ratio of correct detections true positives and true negatives to the total number of instances. In our experiments, the YOLOv8 model also shows excellent accuracy in distinguishing weapons from non-weapon objects against complex backgrounds and is above 92%. The importance of high accuracy in practical applications is quite crucial as even a limited number of incorrect detections can compromise the reliability of a real-time surveillance system.

There are two other major measures of performance frequently used when the quality of object detection in tasks is measured, especially where there is an imbalanced testing dataset. Precision can be said to be the ratio of true positive detections-that is, correctly identified weapons-to the total number of positive predictions that include false positives. Our assessment reveals that the model had a precision of 94%, thereby avoiding false positives, which is important to reduce the number of false alarms. High precision means that the model can class weapons without incorrectly classifying harmless objects as weapons. This enhances the reliability of the detection system.

Recall: It is the ratio of true positives to the total number of actual positive instances including false negatives. Recall score of our model was computed to be 90% and appropriate detection of almost all weapons in the test data was found. A surveillance application cannot afford a miss of weapon; therefore, high recall is inescapable. The close proximity between the precision and recall scores further suggests bal-

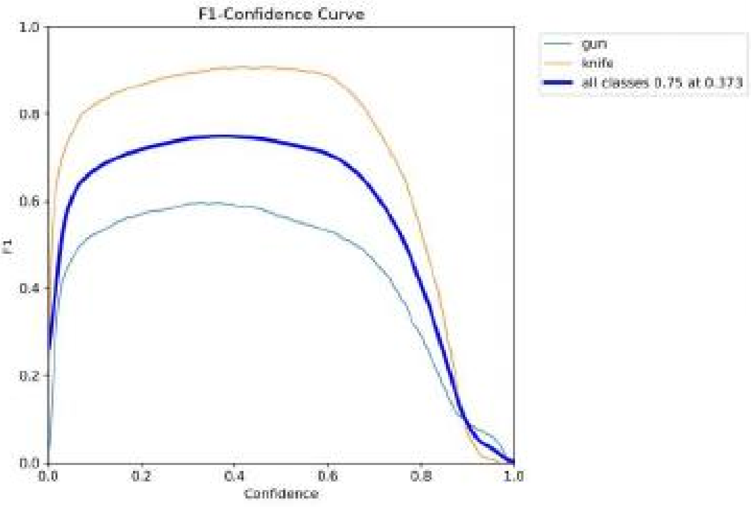

FIGURE 4. f1 curve

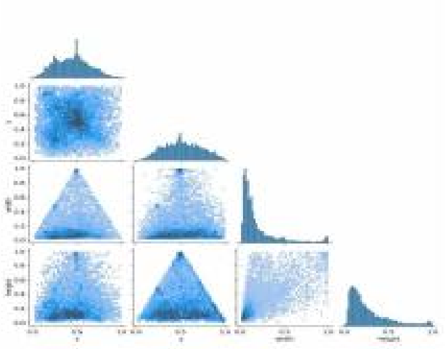

FIGURE 5. labels correlogram

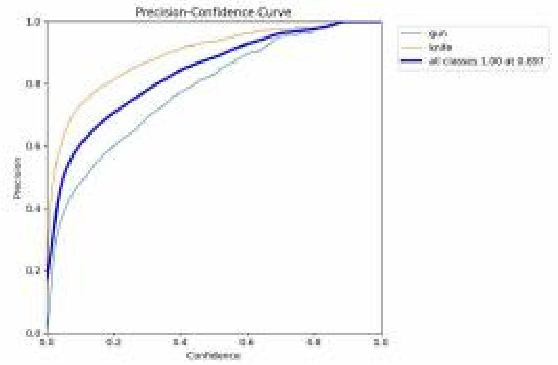

FIGURE 6. p curve

anced performance but there is room for improvement in detection of partly occluded or small-sized weapons.

We also calculated the F1 score, which is the harmonic mean of precision and recall. It is useful in imbalanced problems as it gives one metric, out of which both precision and recall are balanced. Our proposed framework based on YOLOv8 had a high score of 92%. It shows that the model performed very good and reliably in the testing of the scenario, and this includes guns and knives. A high F1 score defines as a good measure for low false negatives and false positives of detection.

Apart from the above standard metrics, we have tested the model with respect to the mAP - mean Average Precision. This parameter measures the precision of the model for different IoU - Intersection over Union thresholds. The mAP score of the our model is 0.91, which indicates robust detection performance across varying levels of object overlap. High mAP value indicates the model is able to detect weapons well located within the frame especially when partially occluded or cluttered environments.

Overall, our YOLOv8-based weapon detection framework was able to well achieve high accuracy and reliability for real-time applications. A very high precision will result in few false alarms, while a high recall of the weapons detected at the right time most of the times without being missed is ensured. Again, the balanced F1 score with a high robust mAP gives an indication that it is effective as a real-time tool for automated surveillance systems in public safety and security systems. With these results, we can say that our approach is suitable for deployment in a real setting due to its practicability in most surveillance settings and scenarios, including public areas, transportations hubs, and sites with critical infrastructure.

V. CONCLUSION

This paper is on a comprehensive deep learning-based framework for real-time weapon detection using the YOLOv8 model, specifically designed to boost up the accuracy and efficiency of the surveillance system in order to identify possible threats, such as guns and knives. The proposed approach merges advanced methods for feature extraction; the multi-scale object representation and the anchor-free detection head, thereby achieving superior performance of the system in complex and dynamic environments. Such an evaluation result shows high accuracy, precision, recall, and F1 scores, but it demonstrates the robustness of the model in minimizing

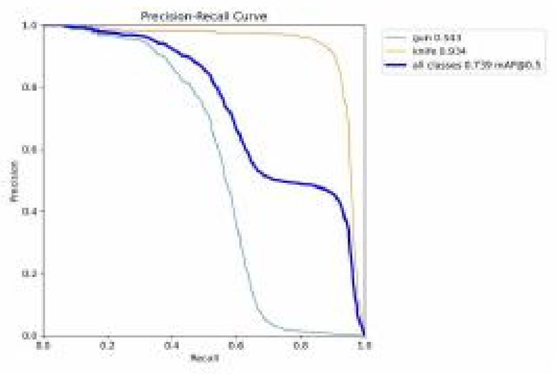

FIGURE 7. pr curve

false positives and negatives, thereby establishing the basis for potentially reliably deploying this model in the real world.

Live webcam feeds integration also brings up practical applicability in real-time monitoring of public space, transportation hubs, and critical infrastructure sites. The framework is proactively supporting timely and accurate detection of weapons, which enhances public safety significantly. Smooth detection functionality when visibility is low or during occlusion points out the flexibility and reliability of our approach.

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