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# Weapon detection system promoting secure city with auto alert system

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**Abstract : Crime is a deed that is based on an offensive act, but to overcome such offensive acts it has always been necessary to utilize different means to minimize them in a short period of time. Some of these crimes result in danger to both the environment and human life. A mobile application will be developed using reactjs for notification on weapon detection. Thus, this project helps in effective detection of weapons at public places in real time applications.**

## I. Introduction

Weapon or anomaly detection is the identification of irregular, unexpected, unpredictable, unusual events or items, which is not considered as a normally occurring event or a regular item in a pattern and thus different from existing patterns.

Violence committed with guns tends to put a consequential impact on the public's social-economic
constructs. Psychological trauma is prevalent among the younger generation who are exposed to higher levels of barbarity in their communities or through the media. Children exposed to gun-related violence, whether they are victims, perpetrators, or witnesses, can experience negative psychological effects over the short and long terms.
Identifying the disruptive behaviors of potential threats at early stage and surveilling the suspicious activities carefully can help reduce crime essentially giving the law enforcement agencies more ammunition to take immediate action

Nowadays, with the accessibility of huge datasets, quicker GPUs, advanced machine learning algorithms, and better calculations, automated computer-based systems can be developed to distinguish and identify numerous items on a site with high accuracy. Developments in recent times in the machine learning industry have proved that advanced image processing algorithms have played a vital role in smart cctv surveillance and security frameworks. In addition to this, the demand of smart devices and IOT cameras has also enriched this domain. However, detection and tracking of humans and weapons are still conducted in the cloud centers, as real-time, online tracking is computationally expensive.

## II. Literature Survey

### A. *Combining Commercially Available Active and Passive Sensors Into a Millimeter-Wave Imager for Concealed Weapon Detection*

***by Federico García-Rial***

The Current imaging technology for concealed weapon detection in the millimeter-wave (mm-wave) and terahertz ranges is traditionally limited to a single type of sensor. In this paper talks about a system which is a combination of active mm-wave sensors and passive mm-wave sensors along with a depth-sensing camera . These sensors are combined at a hardware stage as well as at software level . The images that we obtain as results from each of the individual sensors are then combined using image fusion techniques . Here we use a consumer-grade optical sensor as an image noise-removing tool. Each sensor is able to compensate for some of the imaging limitations of the others, thus offering better overall detection capabilities.

### B. *An Efficient Marginal-Return-Based Constructive Heuristic to Solve the Sensor–Weapon–Target Assignment Problem*

***by Bin Xin***

In network-centric warfare, the interconnections among various combat resources enable an advanced operational pattern of cooperative engagement. The operational effectiveness and outcome strongly depends on the reasonable utilization of available sensors and weapons. In this paper, a mathematical model for the co-allocation of sensors and weapons is built, taking into account the interdependencies between weapons and sensors, the resource constraints, the capability constraints, as well as the strategy constraints. A marginal-return-based constructive heuristic (MRBCH) is proposed to solve the formulated sensor–weapon–target assignment (S-WTA) problem. MRBCH exploits the marginal return of each sensor–weapon–target triplet and dynamically updates the threat value of all targets. It relies only on simple lookup operations to choose each assignment triplet, thus resulting in very low computational complexity. For performance evaluation, we build a general Monte Carlo simulation-based S-WTA framework. Furthermore, we employ a random sampling method and an extension of the state-ofthe-art algorithm Swt_opt as competitors. The computational results show that MRBCH consistently performs very well in solving S-WTA instances of different scales, and it can generate assignment schemes much more efficiently than its competitors.

## III. Existing System

### A. About the existing system

For the public and industrial security surveillance videos is a mandatory task. A lot of growth in the field of computer vision has made it easy to automate the surveillance system in the lines of recognition of human activity, like analysis of behavior and violence detection (VD). First, the input video frames are passed to a lightweight convolutional neural network model for important information collection including humans or suspicious objects such as knives/guns.

### B. Disadvantages of the existing system

In the existing system, the methods are widely based on a single view where the single camera is unable to cover the whole scene.Moreover , the accuracy achieved is very low such that the mAP (mean average precision)is only 46.26%.

## IV. Proposed System

### A. About the proposed system

The proposed system provides an effective solution to determine the weapon detection in a more efficient way. In this project, we have used the Deep Learning algorithm, Yolov7-tiny for weapon detection in CCTV surveillance videos. The datasets were collected from research websites [1] and were trained using deep learning algorithms and the model file was generated. A mobile application was developed using reactjs for the notification of weapon detection. When a weapon such as a gun is detected, a notification is sent to the mobile application with which immediate steps can be taken by the user. When an input image is given for the prediction process, it can easily detect the weapon via CCTV surveillance. Thus, this project helps in effectively detecting the weapon at public places with real time applications.

- Effective solution for weapon detection.
- Using deep learning algorithms to predict the weapon in public places.
- Provides a quick and inexpensive detection of weapons via CCTV surveillance systems.

## V. Module Description

### A. Dataset collection

In this project, we have collected the dataset from Sohas[1] and fed it for training with the deep learning algorithm. Increasing the amount of dataset increases the accuracy.

When there is a good amount of data for training, a deep network can perform extremely well. The more the labeled data we have, the better our model would perform.

### B. Dataset Pre-processing

Data preprocessing is the process of molding the raw data and making it susceptible for a deep learning model. It is the first step and the most important step while working with a deep learning model. Data preprocessing is responsible for transforming the data into a format that is more easily and effectively processed in the steps further ahead like data mining, deep learning tasks etc . The usage of these techniques is usually observed in the beginning stages of the deep learning pipeline itself in order to make sure we have accurate results.

Building a good and efficient neural network model depends on the decisions made with respect to the network architecture and the format of the input data.There are quite a few important image data input parameters used .

For this project ,we chose the following values-

- number of images = 5002 (Training), 857 (Testing)
- image width, image height = [608*608]

### C. Training with deep learning algorithm

The YOLOv7 algorithm used in our project consists of 3 components - backbone, head and neck. Essentially, what happens is when we send an input image into the network, first, the backbone extracts all the essential features of the input image and then feeds them to the Head via the neck. In the neck , the feature maps collected by the backbone are taken and feature pyramids are created from them . Finally , the output , that is , the detected objects that are marked by bounding boxes are obtained at the head. In our case we get the detected weapons in a bounding box at the head . The head has output layers that give us the final detected outputs .

YOLOv7 is better than its previous versions as it comes with certain architectural reforms with the introduction of Extended efficient layer aggregation network and model scaling for concatenation -based models .

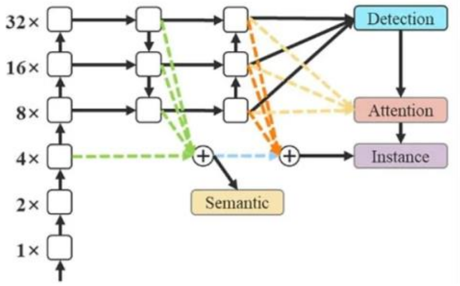


Figure 1 Architectural Diagram

## D. *Validation and Evaluation*

After training with deep learning algorithms, it will validate and evaluate the datasets. Validation in deep learning is like an authorization or authentication of the prediction done by a trained model. It involves assessment of the machine learning model training process and how accurate the detections are given in different situations.

## E. *Prediction of weapon detection*

The main purpose of this research work is to find the best prediction model to detect weapons in CCTV camera surveillance videos. After applying a deep learning algorithm, an input image is given for the weapon detection via CCTV surveillance videos. Thus, this project helps in the effective detection of the weapon at public places in real time applications.

## RESULTS AND DISCUSSION

To begin with, testing of the trained model, we can split our project into modules of implementation that is done.

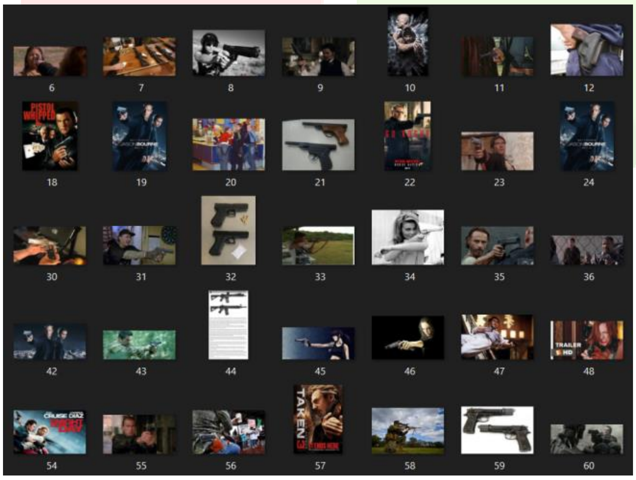

Figure 2 : Dataset

The dataset has been collected for the project and Figure 2 represents the images that have been used for the training process

Then these datasets are pre-processed to convert the images into required size format so that it can be made ready for training with the model.

Figure 3 shows the simple pre-processing techniques used for image resizing using Open CV2 for uniformity and easier annotation of the weapon.

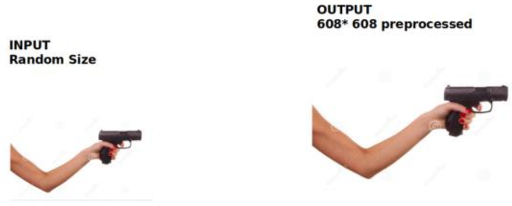


Figure 3 : Image resizing

Figure 4 shows the image annotated using roboflow software


Figure 4 : Image Annotation

The below figure shows the generation of trained yolov7 models for each interval of one epoch.

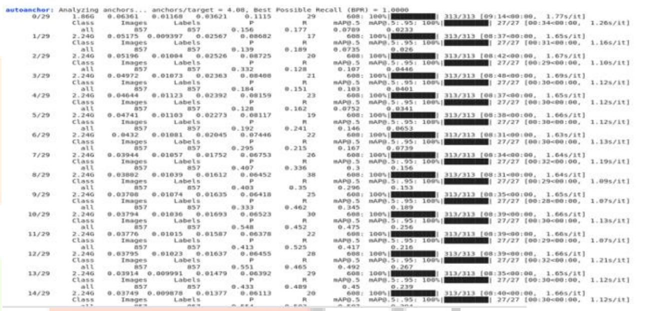

Figure 5 : Trained Models

Figure 6 shows the output of training

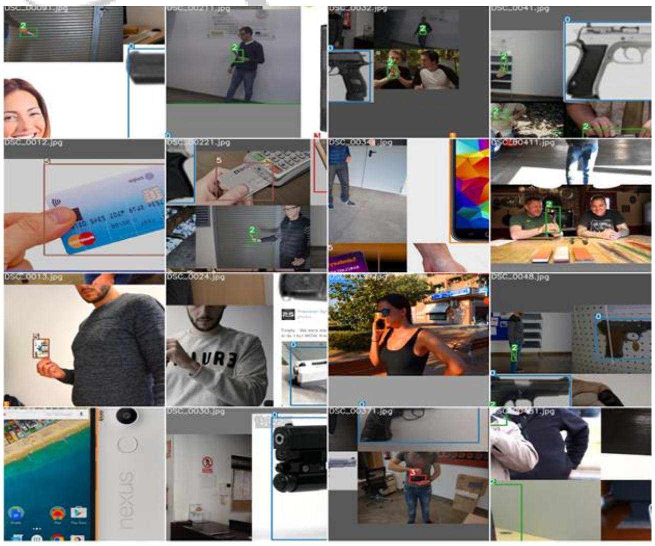

Figure 6

Figure 7 represents the various classes of weapons detected and the subsequent values of precision, recall, and mean average precision have been tabulated.

```
val: Scanning '/content/yolov7/Weapon_Detection_Dataset/obj_train_data/labels/train' images and labels... 5002 found, 0 missing, 0 empty
val: New cache created: /content/yolov7/Weapon_Detection_Dataset/obj_train_data/labels/train.cache
          Class      Images      Labels           P           R      mAP@.5  mAP@.5:.95: 100% 313/313 [02:22<00:00,  2.19it/s]
            all        5002        5002       0.872       0.853       0.911       0.678
         pistol        5002        1425       0.905       0.872        0.93       0.698
     smartphone        5002         575         0.8       0.853       0.863       0.757
          knife        5002        1825       0.882       0.808       0.906       0.531
       monedero        5002         530         0.9       0.915       0.959       0.733
        billete        5002         425       0.861        0.86       0.909       0.658
        tarjeta        5002         222       0.883       0.811       0.896       0.694
Speed: 3.1/2.2/5.3 ms inference/NMS/total per 608x608 image at batch-size 16
Results saved to runs/test/yolov7tiny_custom5_testing
```

Figure 7

Figure 8


Figure 8

The above confusion matrix depicted in figure 8 depicts the number of false positives , false negatives , true positives and true negatives with respect to each class .It can be observed that the correctness in predicting knives and pistols is pretty high and therefore it serves the purpose of our application.

Similarly the correctness and accuracy associated with the prediction of all classes is well depicted in the confusion matrix.

## VI. Conclusion

This paper talks about the application of YOLOv7 tiny as a weapon detection model that can be used in various public places in order to enforce security.

Our model classifies weapons into 6 different classes . Our model currently stands at an accuracy

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