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WEAPON DETECTION USING ARTIFICIAL INTELLIGENCE AND DEEP LEARNING FOR SECURITY APPLICATIONS

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ABSTRACT

Security is always a main concern in every domain, due to a rise in crime rate in a crowded event or suspicious lonely areas. Abnormal detection and monitoring have major applications of computer vision to tackle various problems. Due to growing demand in the protection of safety, security and personal properties, needs and deployment of video surveillance systems can recognize and interpret the scene and anomaly events play a vital role in intelligence monitoring. This paper implements automatic gun (or) weapon detection using a convolution neural network (CNN) based SSD and Faster RCNN algorithms. Proposed implementation uses two types of datasets. One dataset, which had pre-labelled images and the other one is a set of images, which were labelled manually. Results are tabulated, both algorithms achieve good accuracy, but their application in real situations can be based on the trade-off between speed and accuracy.

I. INTRODUCTION

Video surveillance system, which plays a vital role in the security area, is derived from Closed Circuit Television (CCTV), but the data stream mainly flows from the front-end camera to the control centre. It is also called the CCTV system in some literature for this reason. Surveillance cameras were first introduced into Physical Protecting System (PPS) in the field of security to substitute the patrol guard for checking the alarm given by the intrusion detector. Surveillance videos furnished the key clues to identify the suspects and expose their criminal behaviour during the investigation process of the 2005 London bombings. It was the first time that governments realized the significance of the video surveillance system to the security of city life. From then on, video surveillance system becomes one of the essential components of security infrastructures in urban. It obtains a consensus that video surveillance is effective in crime prevention and also in reducing certain crimes to a great extent. According to statistics, robbery, serious assault, and motorcycle theft are the top three types of crime to be monitored and cracked down via video surveillance. For instance, it is recorded that an around 51% reduction lay on the crimes after video surveillance equipped in public places, such as parking lot and street.

II. EXISTING SYSTEM

Security is always a main concern in every domain, due to a rise in crime rate in a crowded event or suspicious lonely areas. Abnormal detection and monitoring have major applications of computer vision to tackle various problems. Due to growing demand in the protection of safety, security and personal properties, needs and deployment of video surveillance systems can recognize and interpret the scene and anomaly events play a vital role in intelligence monitoring. This paper implements automatic gun (or) weapon detection using a convolution neural network (CNN) based SSD and Faster RCNN algorithms. Proposed implementation uses two types of datasets. One dataset, which had pre-labelled images and the other one is a set of images, which were labelled manually that occurs frequently in a scene. This paper reviewed and categorized various algorithms that have been used in the detection of handgun and knives with their strengths and weaknesses. This paper presents a review of various algorithms used in detecting handguns and knives.

III. PROPOSED SYSTEM

TABLE 1: LITERATURE SUMMARY

Sl.No.	TITLE	METHODOLOGY	ADVANTAGES
1	Learning efficient single-stage pedestrian detectors by asymptotic localization fitting	SSD	It is used to detects anchor boxes
2	Report on the Evaluation of 2D Still-Image Face Recognition Algorithms	One-to-many search algorithms are evaluated in terms of their use in both investigational.	It is used to recognise the face
3	Video surveillance systems-current status and future trends	SSD	It is used to detect the objects.
4	PETS 2018: Dataset and challenge	SSD	It is used to find the problems and challenges in the pest dataset

SSD and quicker RCNN algorithms are simulated for pre labelled and self-created image dataset for weapon (gun) detection. each the algorithms are economical and provides sensible results however their application in real time is predicated on a exchange between speed and accuracy. In terms of speed, SSD algorithmic program provides higher speed with 0.736 s/frame. Whereas quicker RCNN provides speed 1.606s/frame, that is poor compared to SSD. With relevancy accuracy, quicker RCNN provides higher accuracy of 84.6%. Whereas SSD provides AN accuracy of 73. 8%, that is poor compared to quicker RCNN.SSD provided real time detection thanks to quicker speed however quicker RCNN provided superior accuracy.

IV. YSTEM IMPLEMENTATION

List of Modules:

1. Data Collection

In this project, data collection for crime intention was collected on images of crime intended using guns. The authors collected data for armed crime intention in public using a public image dataset from the Weapon detection dataset and Weapon detection system.

There is not any particular dataset we can utilise for this investigation. This study will employ mixture of two datasets to get the great results. The initial data set for this study comes from Kaggle which includes 5687 images. Some of these images are already annotated and some are CCTV images without annotation.

After collecting datasets, the authors pre-processed the images in datasets to suit the object detection training methods, then partitioned the dataset into a training set and testing set using the ratio of 80:20 (80 percent partitioned to a training set and 20 percent used as a testing set).

2. Data Pre-processing: There is a text file linked to each image with exact same name but different extension i.e. txt that provides the following information: ’class - center x - center y - width - height’. first digit represents the actual class of the object every class has different color associated with it, center x is the horizontal position of the center of the bounding box divided by the whole width of the photo, center y is the vertical position of the center of the bounding box divided by the whole height of the photo, the width of the bounding box divided by the whole width of image, and the height of the bounding box divided by the whole height of the photo. All these numbers are always between 0 to 1. All of the photographs must be individually labelled, making this the most time-consuming procedure. Although tools like YoloLabel or Labelling might expedite the process, there is no other option except to work over each photo individually.

3. Building Model: Weapon Detection Model Training Weapon detection model training needs informative data to learn the images. The dataset must be prepared correctly. The dataset is composed of the image files and label

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files which indicate the weapon object in the images, which are then partitioned into the training set and testing set. The partitioned dataset is needed to convert into a TF Record file, which is the data file format used for TensorFlow Model Zoo object detection model training.

In the model training process, the divided TF Record files were used for feeding image information through the network. The configuration pipeline file is used for tuning the iteration and other values for model training. The label map file is also needed for indicating the type of objects for the model learning. For evaluating the weapon detection model, the results value will indicate the location of the detected weapon on images and classified object type. To analyse the model correctness, the Mean Average Precision (MAP) and the Intersection over Union (IoU) are involved.

4. Weapon Detection: In this module we are capturing image through the live camera and apply the SSD detector to detect the weapons. If weapon detected system will make alarm.

V. SYSTEM ARCHITECTURE

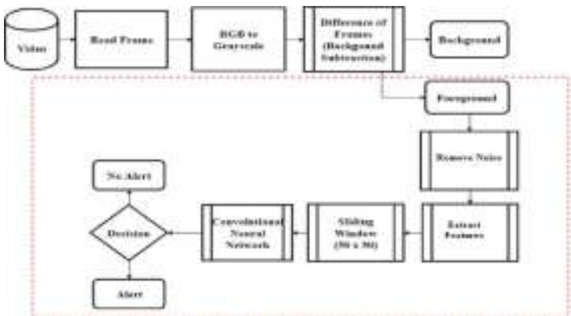

Figure 1: Proposed System Architecture

The below figure 5.1 illustrates the steps in weapon detection system, Data pre-processing first performed in our weapon detection structure, reading frame, RGB to Grayscale, and extracting features processing. Then, convert the vectors and train the algorithm using CNN algorithm.

Faster - RCNN

The drawbacks of R-CNN to build a faster object detection algorithm and it was called Fast R-CNN. The approach is similar to the R-CNN algorithm. But, instead of feeding the region proposals to the CNN, we feed the input image to the CNN to generate a convolutional feature map. From the convolutional feature map, we identify the region of proposals and warp them into squares and by using a RoI pooling layer we reshape them into a fixed size so that it can be fed into a fully connected layer. From the RoI feature vector, we use a softmax layer to predict the class of the proposed region and also the offset values for the bounding box.The reason "Fast R-CNN" is faster than R-CNN is because you don't have to feed 2000 region proposals to the convolutional neural network every time. Instead, the convolution operation is done only once per image and a feature map is generated from it.

VI. RESULTS AND DISCUSSION

The system was created using Windows 10 as well as a 64-bit processor with 8 GB of RAM. The model implemented with the help of Python v3.7.8. The performance of the classification techniques is good with 90% accuracy.

The below figure 2 shows the main screen. Main implementation of the system will b e performed here.

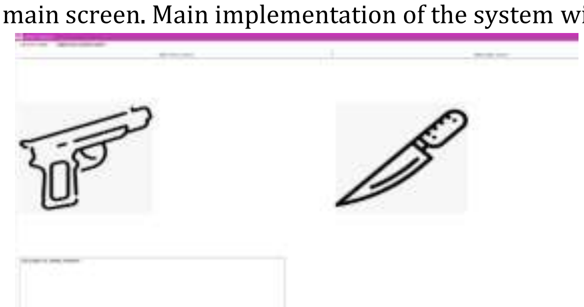

Figure 2: Main Screen

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The figure shown in figure 3 the prediction which starts after the user clicks on "Start Pistol Detection" button.

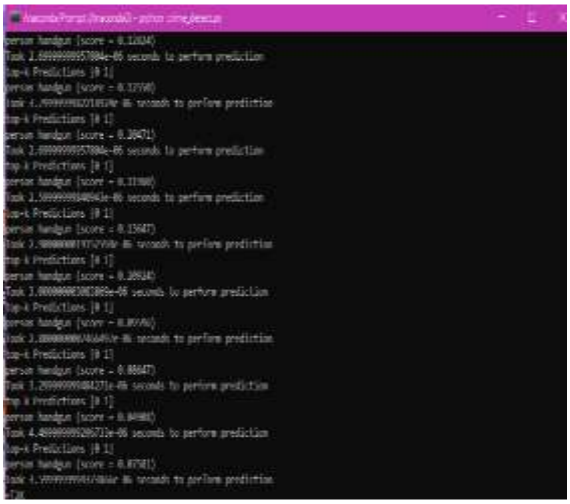

Figure 3: Detection of the Weapon

This figure shows the messages of the phone which comes after the detection of the weapon.

Figure 4: Detection Message

VII. CONCLUSION

Main focus of the study is to predict the weapons in images as well as video files. Both implementations of model using YOLOv4 and Scaled-YOLOv4 were satisfyingly able perform this task. Also, both models employed in this study were able to successfully predict confusion objects along with key ability to predict actual firearm (handgun). Therefore, they can be applied for the use of weapon detection in real world scenarios. Amongst YOLOv4 and Scaled-YOLOv4, YOLOv4 performs slightly better with mean average precision (mAP@0.50) of 86.19%, loss error function of 0.1933, Precision of 79%, and F1-score of 77%.

VIII. FUTURE SCOPE

Future work will focus on further lowering false negatives and positives. System can be integrated with the alerting system to alert concerned authorities in case of weapon detection with high confidence score. We may also attempt to use more training data to gain better results. Additional weaponry can be incorporated as this study solely considers handguns. We may also add more number of common confusion object to add further complexity. We may anticipate more precise outcomes with improved CCTV footage quality.

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