WEAPON DETECTION FROM CROWDED AREAS

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ABSTARCT

Security and safety is a big concern for today's modern world. For a country to be economically strong, it must ensure a safe and secure environment for investors and tourists. Having said that, Closed Circuit Television (CCTV) cameras are being used for surveillance and to monitor activities i.e. robberies but these cameras still require human supervision and intervention. We need a system that can automatically detect these illegal activities. Despite state-of-the-art deep learning algorithms, fast processing hardware, and advanced CCTV cameras, weapon detection in real-time is still a serious challenge. Observing angle differences, occlusions by the carrier of the firearm and persons around it further enhances the difficulty of the challenge. This work focuses on providing a secure place using CCTV footage as a source to detect harmful weapons by applying the state of the art open-source deep learning algorithms. This paper presents a system for gun and knife detection based on the Faster R-CNN methodology. Two approaches have been compared taking as CNN base a GoogleNet and a SqueezeNet architecture respectively. The best result for gun detection was obtained using a SqueezeNet architecture achieving a 85.45% AP50. For knife detection, the GoogleNet approach achieved a 98.68% AP50. Both results improve upon previous literature results evidencing the effectiveness of our detectors. Two approaches are used i.e. sliding window/classification and region proposal/object detection. Some of the algorithms used are VGG16, Inception-V3, Inception-ResnetV2, SSDMobileNetV1, Faster-RCNN Inception-ResnetV2 (FRIRv2), YOLOv3, and YOLOv4. Precision and recall count the most rather than accuracy when object detection is performed so these entire algorithms were tested in terms of them. Yolov4 stands out best amongst all other algorithms and gave a F1-score of 91% along with a mean average precision of 91.73% higher than previously achieved.

1.INTRODUCTION

The use of weapons in public places has become a major problem in our society. These situations are more frequent in countries where weapons are legally purchased or their use is not controlled [10]. Crowded places are especially vulnerable. Unfortunately, mass shootings have become one of the most dramatic problems we face nowadays [20]. Video surveillance systems, typically based on classic closed circuit television (CCTV) are especially useful for intruder detection and remote alarm verification [6]. However, these systems need to be continuously supervised by a human operator. In this respect, it is estimated that the concentration of a security guard watching a camera panel decreases catastrophically after 20 minutes. Security can be increased applying artificial vision algorithms on images obtained from video surveillance systems. Another advantage of these algorithms is the possibility of monitoring larger spaces using fewer devices thus requiring less dependence on the human factor. Machine learning techniques have been widely used in the field of video surveillance. The prevalent paradigm of deep learning has but increased the potential of machine learning in automatic video surveillance. The objective of this work is the development of two novel weapon detectors, for guns and knives, applying deep learning techniques and assess their performance.

2.LITERATURE REVIEW

The applications of the deep learning paradigm for weapon detection are still rather limited. The seminal work of Olmost et al. [14] presented an automatic handgun detection system for video surveillance. This system was based on a Faster R-CNN with a VGG16 architecture trained using their own gun database. Results provided zero false positives, 100% recall and a precision (IoU=0.5) value of 84,21%. In Valldor et al. [17] a firearm detector for application to social media was presented. The detector employed a Faster R-CNN and an Inception v2 network for feature extraction. A public database of images containing several firearms was manually labelled and used for training. Benchmarking was performed on the COCO dataset obtaining a ROC curve that showed usable results. Verma et al. [18] used the Internet Movie Firearm Database (IMFDB) to generate a handheld gun detector. For that purpose, a Faster R-CNN based on a VGG16 architecture was applied only for feature extraction. Classification was performed using three different classifiers: a Support Vector Machine (SVM), a K-Nearest Neighbor (KNN) and a Ensemble Tree classifier. The best result achieved was 93.1% accuracy, using a Boosted Tree classifier. We have to note that the IMFDB dataset contains mostly profile images of pistols and revolvers at high resolution with homogeneous background, which is not a realistic situation. The work of Akcay et al. [5] presented a detection and classification system for X-ray baggage security imagery. The work explored the applicability of multiple detection approaches based on sliding window CNN, Faster R-CNN, Regionbased Fully Convolutional Networks and YOLO. Their system was composed by images divided into six classes: camera, laptop, gun, gun component, knife and ceramic knife. The best results for firearm detection were achieved with a YOLO architecture obtaining a 97.4% AP50. For knife cases, the best results were obtained using a Faster R-CNN based on a ResNet-101 architecture with a 73.2% AP50. Finally, in Kanehisa et al. [11] the YOLO algorithm was applied to create a firearm detection system. The firearm dataset used for this study was extracted from the IMFDB website. Detection results obtained a 95.73% of sensitivity, 97.30% of specificity, 96.26% of accuracy and 70% of mAP50. Regarding knife detection, the most relevant results have been obtained in the context of the COCO (Common Objects in Context) Challenges. COCO is a large-scale object detection dataset focused on detecting objects in context [13]. Each year COCO launches a challenge based on any of the following artificial vision tasks: detection, segmentation, keypoints or scene recognition.

The last object detection challenge using bounding boxes was released in 2017 where the best result for knife detection was obtained by the Intel Lab team. Employing a Faster R-CNN and a HyperNet architecture this team achieved 36.6% AP50. In Yuenyong et al. [19] knife detection was explored using a dataset of 8,527 infrared (IR) images. A GoogleNet architecture was applied to classify IR images as person or person carrying hidden knife. The classification accuracy reported was 97.91%.

In summary, the Faster R-CNN seems to be the prevalent deep architecture for gun and knife detection. This work also focuses on that architecture.

3.METHODOLOGY

As mentioned above, the main objective of this work is the development of an object detector that efficiently locates guns and knives in real-time video. For that purpose, an approach based on deep learning techniques and more specifically through the Faster R-CNN methodology will be adopted. This object detection approach uses internally a CNN and a Regional Proposal Network (RPN) for the classification and location processes respectively. In order to better understand this methodology, a brief description of its evolution and performance is described below.

4.IMPLEMENTATION

Dataset:

The gun dataset has been extracted from [14]. The dataset is composed by 3,000 images of guns from different views and scenarios. In order to increase the accuracy of the detector, a data augmentation technique was applied to the dataset. The aim is to perform transformations that simulate realistic views of the object to be detected, see Figure 1: – Increasing brightness (10%) in order to simulate different illuminations – Image scaling to simulate different distances to the object – Mirroring and rotations (5o) to create different canonical views of the object With these transformations, the dataset was increased to a total of 15,000 images.

On the other hand, the COCO 2017 dataset [1] has been used to train the knife detector. COCO is a large dataset for object detection and segmentation tasks. The full dataset has a total of 330,000 images with 1.5 million objects divided into 80 classes, one of them knives. In the dataset there are a total of 4,326 images of knives, with a total of 7,770 knives labelled. This dataset has been extended by applying the previous transformations for data augmentation so that a total of 23,075 knife images were obtained.

Benchmarking datasets The gun test set was generated leveraging several existing gun datasets with a total of 1,303 images: – The Olmos et al. test set [14] which is composed by a total of 608 images and 304 weapon images. – The small gun category of the Gupta dataset [4] with a total of 80 images of guns. – The handgun class of the Open Images Dataset V4 [3] with 89 images of guns [12]. – Finally, 526 random images from the COCO dataset [1] without weapon instances. Regarding knives, the test set was generated using 169 images from the knife and kitchen knife classes of the Open Images Dataset V4 [3] [12] and 526 random images from the COCO dataset [1] without knives. Thus, the knife test dataset had a total of 695 images.

Following are the steps followed in implementation:

1.Object recognition

- Image classification
- Object localization
- Object detection

2.Classification and detection approach

- Sliding window/classification model
- Region proposal/object detection model

3.Training mechanism

4.Confusion object inclusion

5.EXPERIMENTATION

Dataset contains 1732 images distributed between two classes of pistol and non-pistol with 750 and 982 images in each class respectively. Experimentation on dataset has been performed using the sliding window/classification models of VGG16,Inceptionv3 and InceptionResNetv2.After experimentation we have analyzed that the results obtained are not good because most of the images of this dataset have white or the same kind of the background which lead to a point here the model also starts learning the background as its region of internet and in real-time background varies so a new dataset was required to train and test the model on images it diverse cases and background.

Experimental setup:

Hardware requirements:

Intel(R)Core i3 and above

4GB and higher RAM

500GB Hard Disk

Software requirements:

Python language

PIP Tool

6.RESULT

7. CONCLUSION

Both monitoring and control purposes, this work has presented a novel automatic weapon detection system in real-time. This work ill indeed help in improving the security, law and order situation for the betterment and safety of humanity, especially for the countries ho had suffered a lot with these kinds of violent activities. This will bring a positive impact on the economy by attracting investors and tourists, as security and safety are their primary needs. We have focused on detecting the weapon in live CCTV streams and at the same time reduced the false negatives and positives. To achieve high precision and recall e constructed a ne training database for the real-time scenario, then trained and evaluated it on the latest state-of-the-art deep learning models using two approaches, ie. Sliding window classification and region proposal/object detection. Different algorithm were investigated to get good precision and recall.

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