Weapon Detection using Computer Vision & Artificial Intelligence for Smart Surveillance System

Dr. K Rajitha[1], *K Neelima[2]
[1]Assistant Professor, Mahatma Gandhi Institute of Technology, Hyderabad
[2]Assistant Professor, St. Martin's Engineering College, Secunderabad, Telangana-500100
Email: kneelimait@smec.ac.in

ABSTRACT

Now-a-days, many cases of crimes are reported in public places using different types of weapons such as firearms, swords, cutters, etc. To monitor and minimize such types of crimes, CCTV cameras are installed in public places. Generally, the video footages recorded through these cameras are monitored by security staff. Success and failure of detecting crime depends on the attention of operator. It is not always possible for a person to pay attention on all the video feeds on a single screen recorded through multiple video cameras. We need a system that can automatically detect these illegal activities. 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. No standard dataset was available for real-time scenario. This paper proposes own dataset by making weapon photos from our own camera, manually collected images from internet, extracted data from YouTube CCTV videos etc., Computer vision and Artificial Intelligence methods are used to detect and classify weapon accurately with the goal to reduce crimes and increase safety and security.

Keywords: AI, CCTV, Computer Vision.

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 or items present in a dataset and thus different from existing patterns. An anomaly is a pattern that occurs differently from a set of standard patterns. Therefore, anomalies depend on the phenomenon of interest [3] [4]. Object detection uses feature extract ion and learning algorithms or models to recognize instances of various categories of objects [6]. Proposed implementation focuses on accurate gun detection and classification. Also concerned with accuracy, since a false alarm could result in adverse responses [11] [12]. Choosing the right approach required making a proper trade-off between accuracy and speed. Figure 1 shows the methodology of weapons detection using deep learning. Frames are extracted from the input video. Frame differencing algorithm is applied and bounding box created before the detection of object [7] [8] [14].

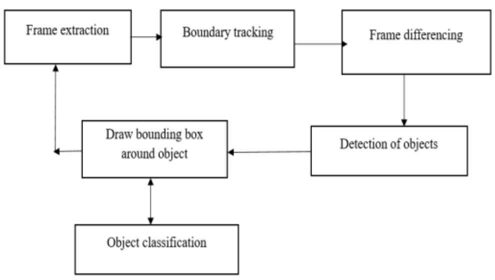

Fig.1.Methodology

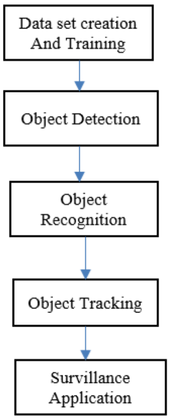

Fig.2. Detection and Tracking

The flow of object detection and tracking as shown in figure 2. Dataset is created, trained and fed to object detection algorithm. Based on application suitable detection algorithm (SSD or fast RCNN) chosen for gun detection. The approach addresses a problem of detection using various machine learning models like Region Convolution Neural Network (RCNN), Single Shot Detection (SSD) [2][9][15].

II. IMPLEMENTATION

A. Resources or components used for implementation

- *Open CV 3.4*- Open source computer vision library version 3.4.
- *Python 3.5*- High level programming language used for various image-processing applications.
- *COCO Dataset*- Dataset consisting of common objects with respective labels.
- *Anaconda and Tensor flow 1.1*
- *NVIDIA GeForce 820M GPU*-Ge Force is a brand of graphics processing units designed by Nvidia.

B. Dataset Specifications

Case – I: Video specifications

- System Configuration- Intel i5 7th Generation (4 Cores)
- Clock Speed- 2.5 GHz
- GPU- NVIDIA GeForce 820M
- Input Frames per Second- 29.97 fps
- Output Frames per Second- 0.20 fps
- Video Format- .move
- Video Size- 4.14 MB
- COCO and self-created image dataset
- Number of classes trained- 5

Case – II: Image specifications

- System Configuration- Intel i5 7th Generation (4 Cores)
- Clock Speed- 2.5 GHz
- GPU- NVIDIA GeForce 820M
- Input Image Size- 200-300 KB
- Training Time- ~0.6seconds (SSD)
- ~1.7 seconds(RCNN)
- Image Format - .JPG
- COCO and self-created image dataset
- Number of classes trained for- 5

C. Assumptions and Constraints made for implementation

- The gun is in line of sight of camera and fully/partially exposed to the camera.
- There is enough background light to detect the ammunition.
- GPU with high-end computation power was used to remove lag in the ammunition detection.
- This is not a completely automated system. Every gun detection warning will be verified by a person in charge.

D. FASTER R-CNN

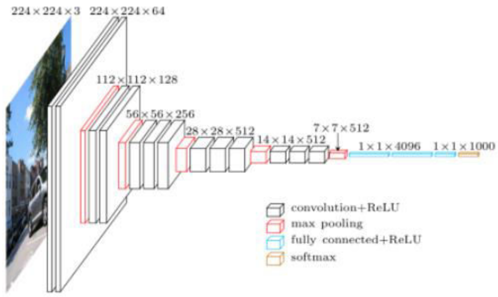

Fig 3. Layers in CNN Architecture [5]

Layers of CNN and faster RCNN architecture depicted in figure 3 and 4 respectively. It has two networks RPN to generate region proposals and network for object detection. To generate region proposals it uses selective search approach. Anchors or region boxes are ranked by RPN network.

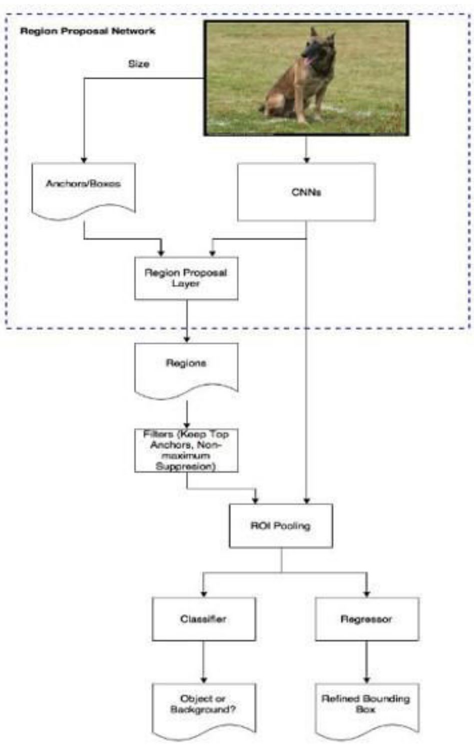

Fig 4. Faster R-CNN [5]

Dataset Creation and Training

Images are downloaded in bulk using Faster Batch Image Downloader (chrome extension) which can download multiple Google Images at once. Then the downloaded images are labeled. 80% of total images used for training and 20% images for testing. The created

ammunition dataset was then trained using Single Shot Detector (SSD) model and made 2669 iterations/steps on the model to ensure that the loss is less than 0.05 in order to increase the accuracy and precision. Figure 5 shows folder with test and train images.
Figure 6 shows image with labels.

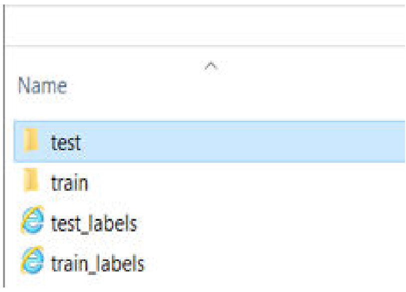

Fig.5. Folder with test and train images

III. RESULTS AND ANALYSIS

A. Detection of weapons using SSD algorithm

Case 1: Using pre-labeled dataset

Fig.18. Detection of AK47 gun

Figure 18. Shows detection of a gun AK47 using SSD algorithm. Accuracy of detection is 79%. Further accuracy can be increased by increasing more number training samples.

Case 2: Using self-created dataset

Fig.19. COLT M1911 Detected wit h 72% accuracy

Fig.20. Smith & Wesson Model Detected wit h 67% accuracy

Figure 19 and 20 shows detection of COLT M1911 and Smith & Wesson Model gun with an accuracy of 72% and 67%

Case 2: Using self-created image dataset

Fig.24. Detect ion of Colt M1911 gun

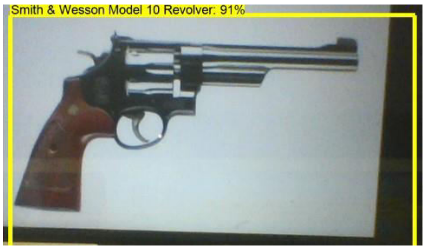

Fig.25. Detect ion of Smith & Wesson Model 10 gun

Figure 24 and 25 shows detection of Colt M1911 gun Smith & Wesson Model 10 gun using Faster R-CNN algorithm with the accuracy of 74% and 91%.

C. *Performance Analysis Faster R-CNN*

TABLE I. PERFORMANCE ANALYSIS: FASTER R-CNN ALGORITHM

Gun Type	Average Accuracy	Speed (S)	Gun Detection	Correct Classification
AK-47	94%	1.28	Yes	Yes
Colt M1911	74%	1.63	Yes	Yes
S&W Model 10	91%	1.74	Yes	Yes
UZI Model	88%	1.49	Yes	No
Remington Model	76%	1.89	Yes	No

From Table 1. It shows that highest average accuracy is obtained for pre-labeled dataset (i.e. AK47) and the Colt M1911, Smith & Wesson Model 10, UZI Model, Remington Model obtained accuracy in the range of 76% to 91%. Faster R-CNN achieves an average Accuracy of 84.6% and average speed 1.606s/frame. This concludes that the pre labeled dataset provided better accuracy because it is trained for millions of images in comparison to the self-created dataset. *SSD*

TABLE II. PERFORMANCE ANALYSIS: SSD ALGORITHM

Gun Type	Average Accuracy	Speed (S)	Gun Detection	Correct Classification
AK-47	80%	0.67	Yes	Yes
Colt M1911	70%	0.89	Yes	Yes
S&W Model 10	66%	0.78	Yes	Yes
UZI Model	81%	0.61	Yes	No
Remington Model	72%	0.73	Yes	No

Table 2 shows performance Analysis for the SSD algorithm.

Obtained SSD Average Accuracy is 73.8% and average Speed 0.736 s/frame. Trained model for 5 classes of guns such asAK47, Smith and Wesson Model 10, Colt M1911, UZI Model and Remington model and obtained maximum confidence level for AK47 gun. Used SSD and RCNN Inception V2 models to train the guns. SSD took 12 more hours to train model in comparison with RCNN model but provided lower accuracy. Faster R-CNN achieved 10.8% more average accuracy than SSD algorithm. SSD provides faster speed than Faster R-CNN by 0.7 seconds. Pre-labeled dataset like AK47 gun provides higher accuracy in SSD and Faster R-CNN models, compared to self-created image dataset.

IV. Conclusions

SSD and Faster RCNN algorithms are simulated for pre labeled and self-created image dataset for weapon (gun) detection. Both the algorithms are efficient and give good results but their application in real time is based on a tradeoff between speed and accuracy. In terms of speed, SSD algorithm gives better speed with 0.736s/frame. Whereas Faster RCNN gives speed 1.606s/frame, which is poor compared to SSD. With respect to accuracy, Faster RCNN gives better accuracy of 84.6%. Whereas SSD gives an accuracy of 73.8%, which is poor compared to faster RCNN.SSD provided real time detection due to faster speed but Faster RCNN provided superior accuracy. Further, it can be implemented for larger datasets by training using GPUs and high-end DSP and FPGA kits [16] [17].

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