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WEAPON DETECTION USING ARTIFICIAL INTELLIGENCE AND DEEP LEARNING FOR SECURITY APPLICATIONS

[1]V.GOPINATH, [2]CH.KARTHEEK, [3]S.JAYANTH KUMAR, [4]K.NARESH NAIK
[1]ASST.PROFESSOR, [2]STUDENT, [3] STUDENT, [4] STUDENT
DEPARTMENT OF INFORMATION TECHNOLOGY,
MATRUSRI ENGINEERING COLLEGE, HYDERABAD, INDIA

Abstract: Security is always a main concern in every domain, due to a rise in crime rate in crowded events or suspicious lonely areas. Abnormal detection and monitoring have major applications of computer vision to tackle variousproblems. Due to growing demand in theprotection of safety, security and personal properties, needs and deployment of videosurveillance systems can recognize and interpret the scene and anomaly events play a vital role inintelligence monitoring. This paper implements automatic gun (or) weapon detection using a convolution neural network (CNN) based SS D 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 labelledmanually. 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

Weapon or Anomaly detection is the identification of irregular, unexpected, unpredictable, unusual events or items, which is not considered as a normally occurring event ora 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. Object detection uses feature extraction and learning algorithms or models to recognize instances of various category of objects. Proposed implementation focuses on accurate gun detection and classification. Also concerned with accuracy, since a false alarm could result inadverse responses. Choosing the right approach required to make a proper trade-off between accuracy and speed. Figure 1 shows themethodology of weapons detection using deep learning. Frames are extracted from the inputvideo. Frame differencing algorithm is applied and bounding box created before the detection ofobject.

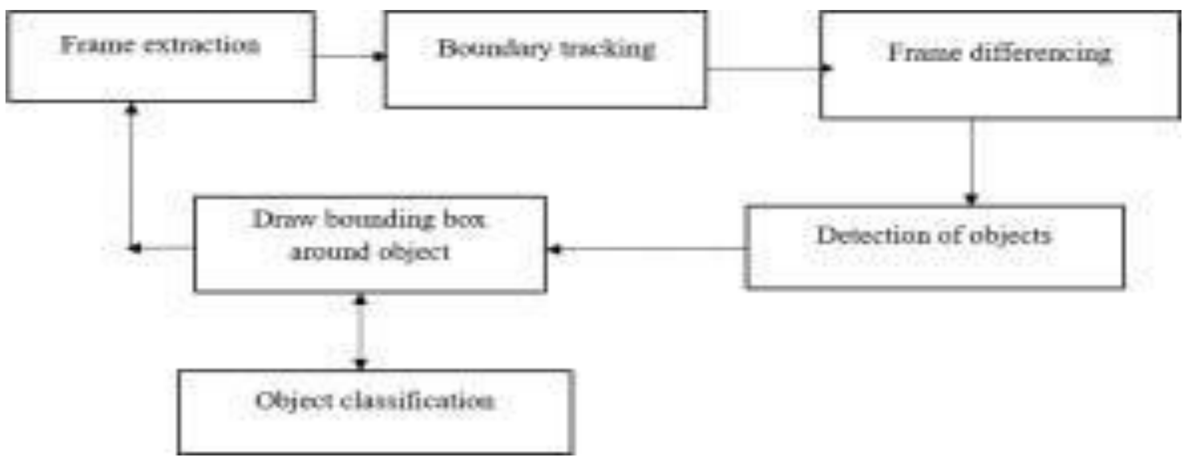


Fig.1.Methodology

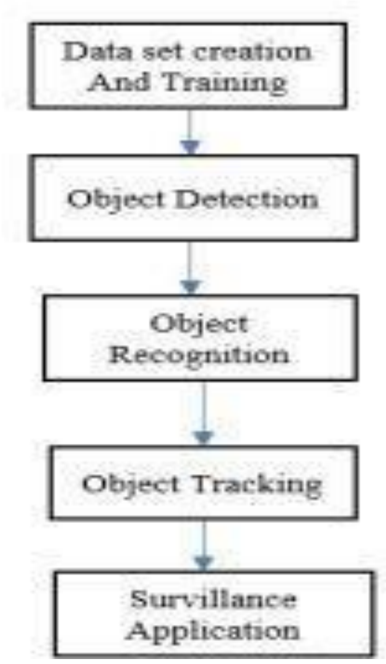


Fig.2. Detection and Tracking

The flow of object detection and tracking as shown in figure 2. Dataset is created, trained andfed 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 usingvarious machine learning models like Region Convolutional Neural Network (RCNN), Single Shot Detection (SSD).

II. SYSTEM ANALYSIS

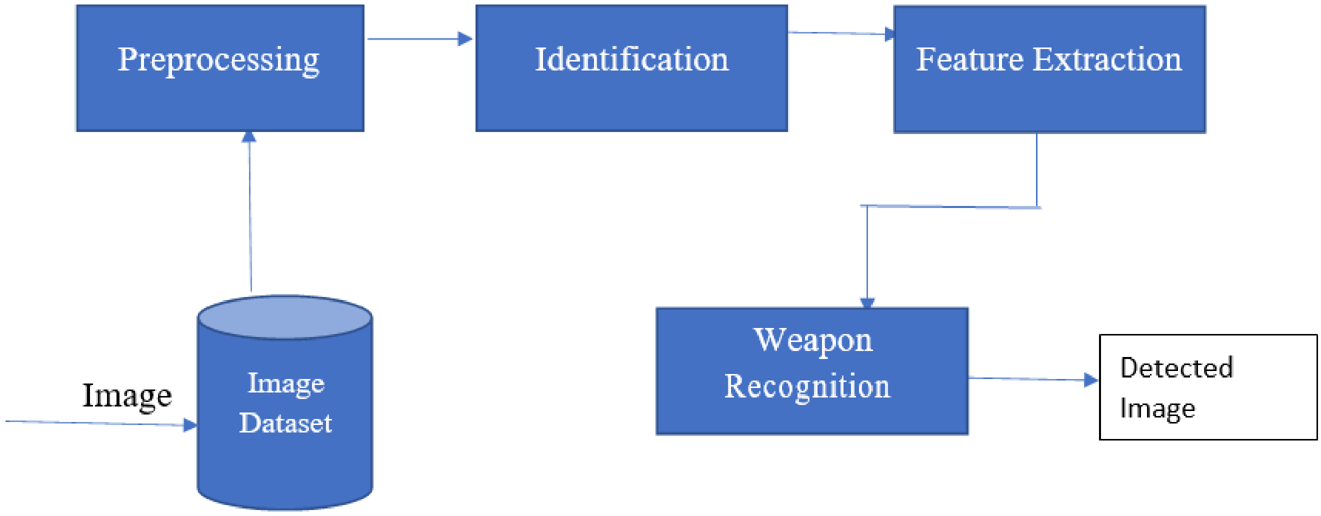
EXISTING SYSTEM:

Weapon or Anamoly detection is the identification of irregular, unexpected, unpredictable, unusual events or items, which is not considered as a normally occurring event ora 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 interes. Object detection uses feature extraction and learning algorithms or models to recognize instances of various category of objects.

PROPOSED SYSTEM:

Proposed implementation focuses on accurate gun detection and classification. Also concerned with accuracy, since a false alarm could result inadverse responses. Choosing the right approach required to make a proper trade-offbetween accuracy and speed. Figure 1 shows themethodology of weapons detection using deep learning. Frames are extracted from the inputvideo. Frame differencing algorithm is applied and bounding box created before the detection ofobject.

SYSTEM ARCHITECTURE



III. IMPLEMENTATION

MODULES DESCRIPTION:

User:

The User can start the project by running mainrun.py file. User must give –input (Video file path). The open cv class Video Capture (0) means primary camera of the system, Video Capture (1) means secondary camera of thesystem. Video Capture (Video file path) means without a camera we can load the video file from the disk. Vgg16 and Vgg19 are programmatically configured. Users can change the model selectionin the code and can run in multiple ways.

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FASTER R-CNN

Layers of CNN and faster RCNN architecture are depicted respectively. It has two networks RPN to generate region proposals and network for object detection. Anchors or region boxes are ranked by RPNnetwork. Dataset Creation and Training Images are downloaded in bulk using Fatkun Batch Image Downloader (chrome extension) which can download multiple Google Images at once. Then the downloaded images are labelled. 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 to increase the accuracy and precision. Figure 5 shows a folder with test and train images. Figure 6 shows an image with labels.

VGG16:

VGG16 is a convolutional neural network model. Deep Convolutional Networks for Large-Scale Image Recognition". The model achieves 92.7% top-5 test accuracy in ImageNet, which isa dataset of over 14 million images belonging to 1000 classes. It was one of the famous model submitted to ILSVRC-2014. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first andsecond convolutional layer, respectively) withmultiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and was using NVIDIA Titan Black GPU's.

Object Detection and Recognition

To make sure object is detected, changes aremade in the label map and tf_record file. Label map is the file which stores the total number of types of objects that will be detected. weapon is added in the label map. It is a popular approach in deep learning where pre-trained models are used as the starting point on computer vision andnatural language processing tasks given the vast compute and Object recognition is refers to a collection of related tasks for identifying objects in digital photographs.

Region-Based Convolutional Neural Networksare a family of techniques for addressing object localization and recognition tasks, designed for model performance. You Only Look Once, or YOLO, is a second family of techniques for object recognition designed for speed and real- time use.

IV. CONCLUSION

SSD and Faster RCNN algorithms are simulated for pre labeled and self-created image dataset forweapon (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 0.736 s/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.

REFERENCES

1. Moez Baccouche, et al. Sequential deep learning for human action recognition. InternationalWorkshop on Human Behavior Understanding. Springer Berlin Heidelberg, 2011.
2. Samir K. Bandyopadhyay, Biswajita Datta, and Sudipta Roy Identifications of concealed weapon in a Human Body Department of Computer Science and Engineer, University of Calcutta, 2012.
3. K. Simonyan, A. Zisserman Very Deep Convolutional Networks for Large-Scale Image Recognition Visual Geometry Group, Department of Engineering Science, University of Oxford, 2015.
4. Greg Flitton, Toby P Breckon, and Najla Megherbi. A comparison of 3d interest point descriptors with application to airport baggage object detection in complex ct imagery. PatternRecognition, 46(9):2420{2436, 2013.
5. Richard Gesick, Caner Saritac, and Chih-Cheng Hung. Automatic image analysis process for the detection of concealed weapons. In Proceedings of the 5th Annual Workshop on CyberSecurity and Information Intelligence Research: Cyber Security and Information Intelligence Challenges and Strategies, page 20. ACM, 2009.
6. Sergio A. Velastin, Boghos A. Boghossian, and Maria Alicia Vicencio-Silva. 2006. A motion-based image processing system for detecting potentially dangerous situations in underground railway stations. Transportation Research Part C: Emerging Technologies 14, 2(2006),96–113.
7. Nadhir Ben Halima and Osama Hosam Bag of words-based surveillance system using vector machines. International Journal of Security and its Applications,2016.
8. Rohit Kumar Tiwari and Gyanendra.A Computer-based framework for visual gun detection using surf. In Electrical, Electronics, Signals, Communication and Optimization (EESCO), 2015 International Conference on, pages 1{5. IEEE,2015Applications,2016.
9. Claire-Hlne Demarty, et. al The MediaEval 2012 affect task: violent scenes detection Working Notes Proceedings of the MediaEval 2012 Workshop. 2012.
10. Yu-Ming Liang, Sheng-Wen Shih, and Arthur Chun-Chieh Shih. 2013. Human action segmentation and classification based on the Isomap algorithm. Multimedia Tools and Applications 62, 3(01Feb2013),561–580.
11. Sergio A. Velastin, Boghos A. Boghossian, and Maria Alicia Vicencio-Silva. 2006. A motion-based image processing system for detecting potentially dangerous situations in underground railway stations. Transportation Research Part C: Emerging Technologies 14, 2 (2006), 96–113.
12. Osama Hosam and Abdulaziz Alraddadi. K-means clustering and support vector machinesapproach for detecting weapons in cluttered scenes. Life Science Journal, 11(9), 2014.