

Application Of Deep Learning For Weapons Detection In Surveillance Videos

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Abstract: Closed-circuit television systems (CCTV) play a vital role in evidence collection against crimes and criminals. The existing systems do not classify normal and abnormal events leading the police to become more reluctant to attend the crime scenes unless there is a visual verification, either by manned patrols or by electronic images from the surveillance cameras. The Proposed work is being used for surveillance, monitoring, and classifications of weapons, live tracking, and many more purposes. In this work, live surveillance videos are taken for monitoring and detecting abnormal events based on real-time image processing techniques. The operations of the proposed project have three processing modules, the first processing module is for object detection using Convolutional Neural Networks(CNN) and the second processing module will handle the classification of weapons, monitoring and alarm operations will be carried out by the third processing module. CCTV will monitor the circular area and it will automatically perform all operations and be controlled. Shape detection algorithms and object detection algorithms have been tested to find accuracy in the detection and analysis of the processing time before implementation in such an environment and results provide optimal accuracy in matching weapons and object types with names and shapes in predefined databases like ALEXNET. The proposed work drastically reduces the crime rate and it also provides a higher level of security in certain areas and it reduces the time required to catch the criminal.

I.INTRODUCTION

The crime rate across the globe has increased mainly because of the frequent use of handheld weapons during violent activity. For a country to progress, the law-and-order situation must be in control. Whether we want to attract investors for investment or to generate revenue with the tourism industry, all these needs is a peaceful and safe environment. The crime ratio because of guns is very critical in numerous parts of the world. It includes mainly those countries in which it is legal to keep a firearm. The world is a global village now and what we speak or write has an impact on the people. Even if the news they heard is crafted having no truth but as it gets viral in a few hours because of the media and especially social media, the damage will be done. People now have more depression and have less control over their anger, and hate speeches can get

those people to lose their minds. People can be brainwashed and psychological studies

show that if a person has a weapon in this situation, he may lose his senses and commit a violent activity. Weapon or Anomaly detection is that the identification of irregular, unexpected, unpredictable, uncommon events or things, that isn't thought-about as a usually occurring event or a daily item in a very pattern or things gift in a very dataset and so totally different from existing patterns. Associate in Nursing anomaly could be a pattern that happens otherwise from a collection of ordinary patterns. Therefore, anomalies rely on the development of interest . Object detection uses feature extraction and learning algorithms or models to acknowledge instances of assorted class of objects. planned implementation focuses on correct gun detection and classification.

additionally involved with accuracy, since a warning may end in adverse responses . selecting the proper approach needed to create a correct trade-off between accuracy and speed. within the methodology of weapons detection exploitation deep learning. Frames ar extracted from the input video. Frame differencing algorithmic program is applied and bounding box created before the detection of object.The flow of object detection and trailing is finished as, Dataset is formed, trained and fed toobject detection algorithmic program. supported application appropriate detection algorithmic program (SSD or quick RCNN) chosen for gun detection.

II.LITERATURE REVIEW

Previous studies on concealed dangerous equipment detection are mainly based on X-ray imagery technology in the framework of “feature extraction + shallow-learning classifier”. Zhang and Zhu presented a bag-of-words (BoW)-based local semantic features extraction method combined with an SVM classifier for detecting dangerous articles in baggage X-ray images. Zhang further utilized SIFT and SURF algorithms to enhance the feature discrimination. Turcsany et al designed an improved BoW representation scheme for detecting firearms in baggage X-ray images by using a class-specific feature clustering algorithm to improve the features distinction of different classes. In the early 1990s, LeCun et al proposed LeNet which has demonstrated excellent performance in hand-written digit classification tasks. In the 2012 ILSVRC classification challenge, Krizhevsky et al won the championship by using the AlexNet that achieved a top-5 test error rate of 15.3% on the ImageNet classification. From then on, the AlexNet has been successfully applied to many computer vision tasks, for instance, to object tracking, object detection, human pose estimation, video classification, and super segmentation. VGGNet and GoogLeNet both

got high performances in the 2014 ILSVRC classification challenge. By utilizing deeper and wider networks, the ability of the networks was improved significantly. Especially, the GoogLeNet with the Inception structure can obtain a better performance on the image classification task by using fewer parameters compared to its predecessor AlexNet. Recently, several much deeper CNNs have been developed, such as the ResNet and DenseNet , which have shown more excellent performance in the tasks of classification and detection.

III.IMPLEMENTATION

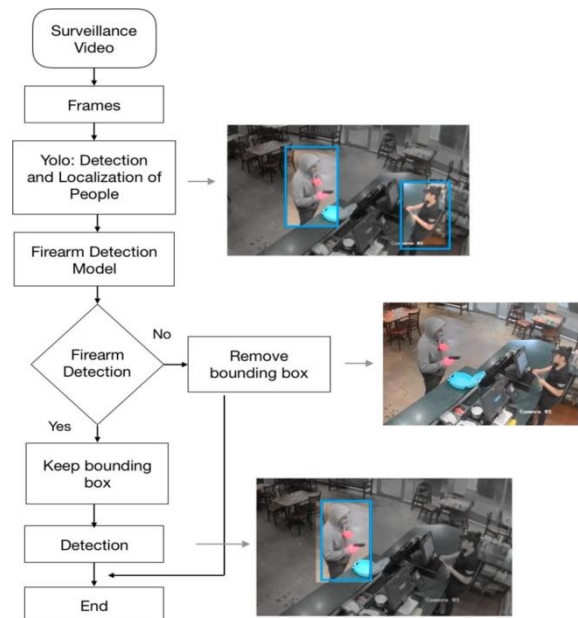


Fig-3: System Architecture

Moduledescription

ImageAcquisition

High-quality Dangerous Objects dataset used. The entire sample set is divided into three parts: training samples and validation samples in the training phase and testing samples in the testing phase. Moreover, the sample set is divided into positive and negative samples a positive sample is an image showing patient behaviors, whereas a negative sample is a background image.

Annotated Dataset Collection

A Knowledge-based dataset is created by proper labeling of the collected images with unique classes.

Image Processing

The obtained images that will be engaged in a preprocessing step are further enhanced specifically for image features during processing. The segmentation process divides the images into several segments and utilized in the extraction of Dangerous Objects from dataset.

Feature Extraction

This section involves the convolutionary layers that obtain image features from the resize images and is also joined after each convolution with the ReLU. Ultimately, both the convolutional and the pooling layers act as purifiers to generate those image characteristics.

Classification

The final step is to classify images, to train deep learning models along with the labeled images to be trained on how to recognize and classify images according to learned visual patterns. The authors used an open-source implementation via the TensorFlow module, using Python and OpenCV including the CNN model.

Algorithm

The various deep learning methods use data to train neural network algorithms to do a variety of machine learning tasks, such as the classification of different classes of objects. Convolution neural networks are deep learning algorithms that are very powerful for the analysis of images. CNN is a powerful algorithm for image processing. These algorithms are currently the best algorithms we have for the automated processing of images. Many companies use these algorithms to do things like identifying the objects in an image. Convolution Neural Networks specialized for applications in image & video recognition. CNN is mainly used in image analysis tasks like Image

recognition, Object detection & Segmentation. Convolution neural network (CNN) is a type of deep neural network, mainly used for image and video. CNN consists of filters as its basic computational component. The advantage of CNN is that it can automatically learns the filters from the training images. The spatial pattern of an image learned by CNN model helps it to recognize and localize the object in the image. There are three types of layers in Convolution Neural Networks:

- Convolutional Layer: In a typical neural network each input neuron is connected to the next hidden layer. In CNN, only a small region of the input layer neurons connect to the neuron hidden layer.
- Pooling Layer: The pooling layer is used to reduce the dimensionality of the feature map. There will be multiple activation & pooling layers inside the hidden layer of the CNN.
- Fully-Connected layer: Fully Connected Layers form the last few layers in the network. The input to the fully connected layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer

IV.RESULT

Types of Weapons Detected In Different Videos

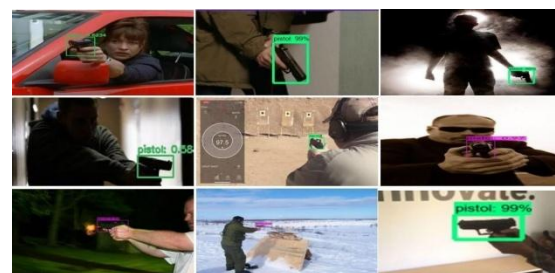


Fig-7.6: This output shows the types of weapons detected in the different videos.

V.CONCLUSION

The weapon detection using YOLOv3 architecture is implemented and trained with the Sohas weapon dataset. The original YOLOv3 model is improved and optimized to increase its performance for detecting small weapon object that include knife and pistol. The YOLOv3 anchor box parameters are optimized with the use of K-Mean clustering method. Both the original and improved YOLOv3 shows good accuracy on the Sohas evaluation dataset. For both monitoring and control purposes, this work has presented a novel automatic weapon detection system in realtime. This work will indeed help in improving the security, law and order situation for the betterment and safety of humanity, especially for the countries who had suffered a lot with these kind 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 we constructed a new 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, i.e. sliding window/classification and region proposal/object detection.

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