WEAPON DETECTION USING ARTIFICIAL INTELLIGENCE

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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 SS Dand 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.

Index Term:-CNN,RCNN,SSDand,opencv

I Introduction

Weapon or Anamoly 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. 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 in adverse responses. Choosing the right approach required to make 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. Fig.1.Methodology Fig.2. Detection and T racking 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 machinelearning models like Region Convolutional Neural Network (RCNN), Single Shot Detection.

2 Literature survey

2.1 Wei Liu et al., "SSD: Single Shot MultiBox Detector", European Conference on Conputer Vision, Volume 169, pp 20-31 Sep. 2017.

Conventionally used cement –a primary binder also a necessitate element in producing concrete rates first in the construction industry. Production of conventional cement requires a greater skill and is energy intensive. The usage of waste materials in the production of concrete and reduction in cement content was only the possible alternative in the past decade. Associated risks with the production of Ordinary Portland Cement are well known. A greener aided with a natural friendly claim can be

made only with the usage of the waste materials and reduction in evolving respiration gas to the atmosphere. Almost all works are carried out using source material fly ash, with fine aggregate and coarse aggregate. Concrete plays a vital role in the construction industry and on the other hand, river sand; one of the essential material has become very expensive which is a scarce material. Depletion of sand is a hectic issue due to increased usage of sand in construction. No other replacement materials such as quarry rock dust is not concentrated in casting geopolymer specimens. Even though in some research papers the replacement materials are added only in partial replacement without aiming on 100% replacement. Many researches mainly focus towards test results of GPC specimens using steel fibers, glass fibers. But the study related to natural fibers and hybrid fibers are found scarce. The main part of this work aimed at characterizing the engineering strength properties of geopolymer concrete by 100% replacement of fine aggregate with quarry rock dust. Hence, combination of flyash and quarry rock dust in GPC have been considered for evaluating the mechanical properties of geopolymer concrete. Also, investigation focuses on incorporation of three different fibers namely polypropylene fibers(PF), coir fibers(CF) and hybrid fibers(HF) in different percentage of proportions such as 0.5%,1%,and 1.5% to determine the maximum strength properties of GPC.2.2 D. Erhan et al., “Scalable Object Detection Using Deep Neural Networks,” IEEE Conference on Computer Vision and Pattern Recognition(CVPR),2014. Deep convolutional neural networks have recently achieved state-of-the-art performance on a number of image recognition benchmarks, including the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC-2012). The winning model on the localization sub-task was a network that predicts a single bounding box and a confidence score for each object category in the image. Such a model captures the whole-image context around the objects but cannot handle multiple instances of the same object in the image without naively replicating the number of outputs for each instance. In this work, we propose a saliency-inspired neural network model for detection, which predicts a set of class-agnostic bounding boxes along with a single score for each box, corresponding to its likelihood of containing any object of interest. The model naturally handles a variable number of instances for each class and allows for cross-class generalization at the highest levels of the network. We are able to obtain competitive recognition performance on VOC2007 and ILSVRC2012, while using only the top few predicted locations in each image and a small number of neural network evaluations. Object detection is one of the fundamental tasks in computer vision. A common paradigm to address this problem is to train object detectors which operate on a subimage and apply these detectors in an exhaustive manner across all locations and scales. This paradigm was successfully used within a discriminatively trained Deformable Part Model (DPM) to achieve state-of-art results on detection tasks [6]. The exhaustive search through all possible locations and scales poses a computational challenge. This challenge becomes even harder as the number of classes grows, since most of the approaches train a separate detector per class. In order to address this issue a variety of methods were proposed, varying from detector cascades, to using segmentation to suggest a small number of object hypotheses [14, 2, 4]. In this paper, we ascribe to the latter philosphy and propose to train a detector, called “DeepMultiBox”,’ which generates a few bounding boxes as object candidates. These boxes are generated by a single DNN in a class agnostic manner. Our model has several contributions. First, we define object detection as a regression problem to the coordinates of several bounding boxes. In addition, for each predicted box the net outputs a confidence score of how likely this box contains an object. This is quite different from traditional approaches, which score features within predefined boxes, and has the advantage of expressing detection of objects in a very compact and efficient way. The second major contribution is the loss, which trains the bounding

box predictors as part of the network training. For each training example, we solve an assignment problem between the current predictions and the groundtruth boxes and update the matched box coordinates, their confidences and the underlying features through Backpropagation. In this way, we learn a deep net tailored towards our localization problem. We capitalize on the excellent representation learning abilities of DNNs, as recently exeplified recently in image classification [10] and object detection settings [13], and perform joint learning of representation and predictors. Finally, we train our object box predictor in a classagnostic manner. We consider this as a scalable way to enable efficient detection of large number of object classes. We show in our experiments that by only post-classifying less than ten boxes, obtained by a single network application, we can achieve state-of-art detection results. Further, we show that our box predictor generalizes over unseen classes and as such is flexible to be re-used within other detection problems. 2. Previous work The literature on object detection is vast, and in this section we will focus on approaches exploiting class-agnostic ideas and addressing scalability. Many of the proposed detection approaches are based on part-based models [7], which more recently have achieved impressive performance thanks to discriminative learning and carefully crafted features [6]. These methods, however, 1 arXiv:1312.2249v1 [cs.CV] 8 Dec 2013 rely on exhaustive application of part templates over multiple scales and as such are expensive. Moreover, they scale linearly in the number of classes, which becomes a challenge for modern datasets such as ImageNet. To address the former issue, Lampert et al. [11] use a branch-and-bound strategy to avoid evaluating all potential object locations. To address the latter issue, Song et al. [12] use a low-dimensional part basis, shared across all object classes. A hashing based approach for efficient part detection has shown good results as well. A different line of work, closer to ours, is based on the idea that objects can be localized without having to know their class. Some of these approaches build on bottom-up classless segmentation. The segments, obtained in this way, can be scored using top-down feedback. Using the same motivation, Alexe et al. use an inexpensive classifier to score object hypotheses for being an object or not and in this way reduce the number of location for the subsequent detection steps. These approaches can be thought of as Multi-layered models, with segmentation as first layer and a segment classification as a subsequent layer. Despite the fact that they encode proven perceptual principles, we will show that having deeper models which are fully learned can lead to superior results. Finally, we capitalize on the recent advances in Deep Learning, most noticeably the work by Krizhevsky et al. We extend their bounding box regression approach for detection to the case of handling multiple objects in a scalable manner. DNN-based regression, to object masks however, has been applied by Szegedy et al. This last approach achieves state-of-art detection performance but does not scale up to multiple classes due to the cost of a single mask regression. 3. Proposed approach We aim at achieving a class-agnostic scalable object detection by predicting a set of bounding boxes, which represent potential objects. More precisely, we use a Deep Neural Network (DNN), which outputs a fixed number of bounding boxes. In addition, it outputs a score for each box expressing the networkconfidence of this box containing an object. Model To formalize the above idea, we encode the i-th object box and its associated confidence as node values of the last net layer: Bounding box: we encode the upper-left and lower-right coordinates of each box as four node values, which can be written as a vector li ∈ R 4 . These coordinates are normalized w. r. t. image dimensions to achieve invariance to absolute image size. Each normalized coordinate is produced by a linear transformation of the last hidden layer. Confidence: the confidence score for the box containing an object is encoded as a single node value ci ∈ [0, 1]. This value is produced through a linear transformation of the last hidden layer followed by a sigmoid. We can

combine the bounding box locations li ,i∈ {1, . . . K}, as one linear layer. Similarly, we can treat collection of all confidences ci ,i∈ {1, . . . K} as the output as one sigmoid layer. Both these output layers are connected to the last hidden layers. At inference time, out algorithm produces K bounding boxes. In our experiments, we use K = 100 and K = 200. If desired, we can use the confidence scores and non-maximum suppression to obtain a smaller number of high-confidence boxes at inference time. These boxes are supposed to represent objects. As such, they can be classified with a subsequent classifier to achieve object detection. Since the number of boxes is very small, we can afford powerful classifiers. In our experiments, we use another DNN for classification. Training Objective We train a DNN to predict bounding boxes and their confidence scores for each training image such that the highest scoring boxes match well the ground truth object boxes for the image. Suppose that for a particular training example, M objects were labeled by bounding boxes gj , j ∈ {1, . . . , M}. In practice, the number of predictions K is much larger than the number of groundtruth boxes M. Therefore, we try to optimize only the subset of predicted boxes which match best the ground truth ones. We optimize their locations to improve their match and maximize their confidences. At the same time we minimize the confidences of the remaining predictions, which are deemed not to localize the true objects well.

3 Implementation Study

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.

3.1proposed methodology

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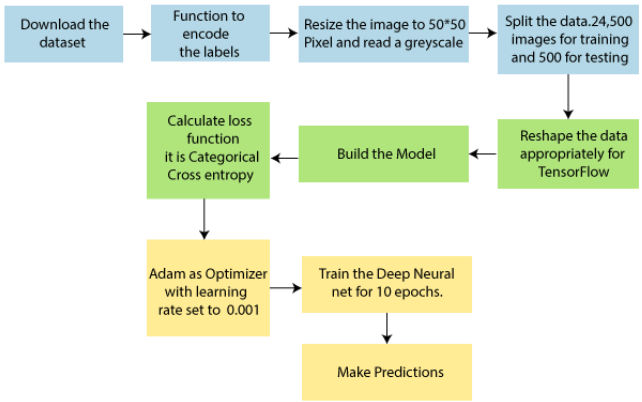

Fig 1: proposed model

4 Results and Evolution Metrics

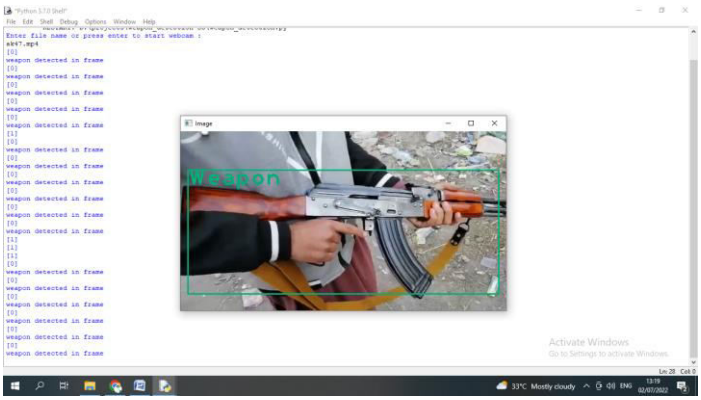

Fig 2:_ In the below screen the weapon is detected and boxing it.

Fig 3 After entering file name the program starts detecting the weapon in video and boxing the object

5 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 0.736 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.

6 References

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