EFFECTIVE USAGE OF ARTIFICIAL INTELLIGENCEAND DEEP LEARNING FOR IMPLEMENTING WEAPON DETECTION FOR SECURITY APPLICATIONS

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ABSTRACT

Because crime tends to spike in busy places or in suspiciously empty ones, security is always an important issue in any field. A number of issues may be addressed via the use of computer vision, particularly in the areas of abnormal detection and monitoring. Intelligence monitoring relies heavily on video surveillance systems that can identify and understand the scene, as well as abnormal occurrences, to meet the rising need for safety, security, and personal property protection. Automatic gun or weapon identification is implemented in this study utilising Faster RCNN and SSD, two techniques based on convolutional neural networks (CNNs). Two kinds of datasets are used in the proposed implementation. There was one dataset with photographs that had already been tagged, and another with images that were to be labelled by hand. Both methods attain high accuracy, and the results are tabulated. However, their practical applicability may depend on the compromise between speed and precision.

INTRODUCTION

Anamoly detection, also known as weapon detection, is the process of spotting anything out of the ordinary in a dataset, such as an occurrence that does not fit the typical pattern or an object that is not part of the regular pattern. A pattern that deviates from a predetermined set of norms is called an anomaly. Thus, the phenomena of interest determines whether there are anomalies. In order to identify examples of different types of things, object detection makes use of extracted features and learning models or algorithms. The accuracy of gun detection and categorization is the main emphasis of the proposed implementation. Also worried about precision, as unintended consequences may ensue from a false warning. Finding a happy medium between precision and speed necessitated picking the correct strategy. The input video is used to extract frames. Prior to object identification, the bounding box is formed and the frame differencing technique is used.

RELATED WORK

"SSD: Single Shot Detector"

We provide a technique that employs just one deep neural network to identify visual objects. Our method, which we call SSD, uses a variety of aspect ratios or scales each feature map position to discretize the output space or bounding boxes into an assortment of default boxes. During the prediction process, the network determines how well each default box fits the form of the item and assigns points based on the existence of each object type. To handle objects of varied sizes naturally, the network also incorporates predictions from numerous map features with different resolutions. Compared to approaches that rely on object proposals, SSD is more straightforward since it consolidates all processing into a single network, doing away with the need to generate proposals and the following phases of pixel or feature resampling. This facilitates the training process and the integration of SSD into systems requiring a detection component. With an integrated structure for training and inference, SSD outperforms approaches that use an extra object proposal phase in terms of speed and accuracy, according to experimental findings on the the PASCAL VOC, COCO, or ILSVRC datasets. **"Scalable Object Detection Using Deep Neural Networks,"**

The ImageNet Massive Visual Identification Challenge (ILSVRC-2012) is only one of many image recognition benchmarks where deep convolution neural network models have lately attained state-of-the-art performance. A network that can identify different types of objects in a picture and then forecast their bounding boxes and confidence scores was the most successful model in the localization sub-task. This kind of model is great for capturing the surrounding environment of an item in a picture, but it is foolish to think it can manage more than one instance of a single object without producing the same amount of outputs. Our proposed detection technique is based on a saliency-inspired neural network. It provides a collection of class-agnostic bounding boxes and assigns a score to each box based on its probability of holding an item of interest. At its most advanced levels, the model is able to generalise across classes and automatically manages an adjustable number of instances per class. We achieve competitive recognition results on VOC2007 and ILSVRC2012 utilising a modest number of artificial neural network evaluations and using just the top 10 predicted locations for each picture.

"Anomaly Detection in Videos for Video Surveillance Applications Using Neural Networks,"

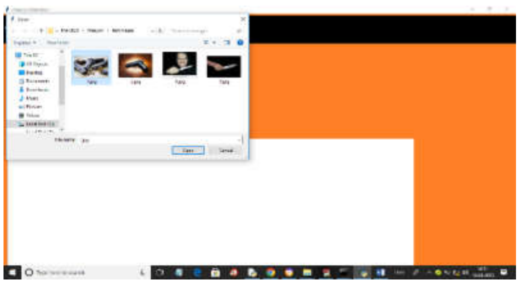
Anomaly detection in videos for video surveillance applications using neural networks refers to the process of automatically identifying irregular or unexpected events within a continuous stream of video data captured by surveillance cameras. Traditional video surveillance systems often rely on predefined rules or handcrafted features to detect anomalies, which can be limited in their ability to adapt to complex scenes or subtle anomalies. An approach to pattern recognition known as anomaly detection may quickly identify outliers—patterns that deviate significantly from the norm. Several plausible outliers may be caught on camera by surveillance systems. Separating the process into its component parts—video labelers, processing of images, and activity detection—allows for more accurate recognition of anomalies in video surveillance. As a consequence, when it comes to real-time situations, anomaly detection in videos in video surveillance applications guarantees outcomes.

"Performance Analysis of Object Detection and Tracking Algorithms for Traffic Surveillance Applications using Neural Networks,"

Using the principles of convolution layers, one object detection was successfully executed. Among the many layers that make up a neural network are the input, hidden, and output layers. When doing single object detection, the dataset used is that of the on-road car dataset. Heavy, Auto, and Light are the three picture categories that make up this dataset. The pictures in the collection have different levels of light. The day, evening, and night datasets have all had their performance metrics computed. The You Only Looked Once (YOLOv3) method has been used for multiple item identification. One deep neural network with convolution is used in this method; the input is divided into a cell grid, and each cell immediately predicts a border box and classes the item. For the purpose of multiple object detection, the KITTI dataset is used. There are a total of 80 classes in it, but just five—car, bus, truck, motorbike, and train—have been viewed for this project. Vehicle tracking was further integrated using the principles of Multiple Object Detection. Multi object detection was applied to the first frames of the video, and the item was tracked in subsequent frames by using its centroid location. The object identification phase was built using the YOLOv3 method in Python and OpenCV.

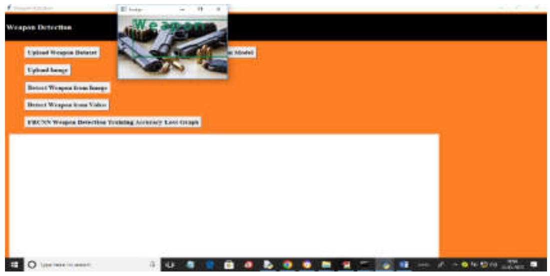
METHODOLOGY

In this research, we provide an implementation of the based SS D and quicker RCNN algorithms for automated weapon identification. Two kinds of datasets are used in the proposed implementation. There was one dataset with photographs that had already been tagged, and another with images that were to be labelled by hand. Both methods attain high accuracy, and the results are tabulated. However, their practical applicability may depend on the



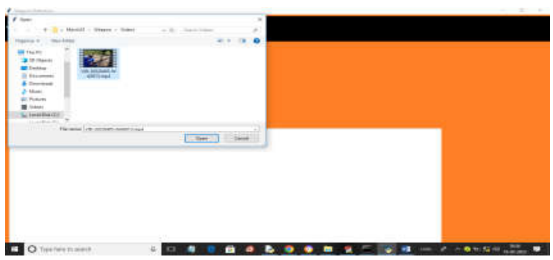
trade-off among speed and precision.

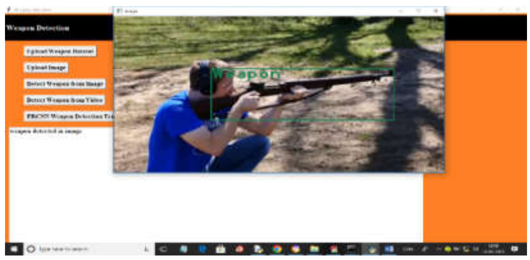
RESULTS AND DISCUSSION



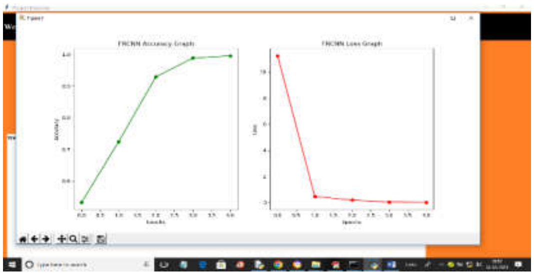
After choosing and uploading a picture to the previous page, you may get the following result by clicking the "Open" and "Detect Weapon from Image" buttons.

You can see that a weapon has been recognised in the picture up there. To do the same with a video file, just click the "Detect Weapon from Video" option. The results will be shown below.





If your system is fast, the video will play quickly; otherwise, it will take some time. To begin playing the video, pick and upload an MP4 file, and then click the "Open" button.You can see the video starting to play and the detection output on the previous



screen. To view the output below, click on the accuracy, achieving an impressive 84.6%. In contrast to the quicker RCNN, SSD only achieves a 73.8% accuracy rate.The quicker speed of SSD allowed for real-time detection, "FRCNN Weapon Identification Training Accuracy-Loss Graph" button.

The x-axis of the training graph above shows the epochs of training, while the y-axis shows the values of accuracy and loss; the green line shows the accuracy and the red line shows the loss. As the epochs grow, the accuracy increases and the loss decreases. Other photographs may also be uploaded and tested in a similar manner.

CONCLUSION

For the purpose of weapon (gun) identification, we simulate the SSD and quicker RCNN algorithms on both pre-labeled and self-created picture datasets. There is a compromise between rapidity and precision when using both methods in real time, but they are efficient and provide decent results. While comparing algorithms, the SSD approach provides faster results, at 0.736 s/frame. In contrast, SSD achieves a speed of 1.606s/frame, whereas Faster RCNN falls far short. Faster RCNN outperforms the other methods in terms.while the better accuracy of quicker RCNN was evident. Additionally, it may be trained using GPUs и elite DSP and FPGA packages, allowing it to be deployed for bigger datasets.

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