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Utilizing Artificial Intelligence and Deep Learning for Weapon Detection in Security Applications

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ABSTRACT— Due to an increase in crime rate at busy events and in lonely, dangerous regions, protection is always a top priority in all fields. Detection and monitoring of anomalies are two of the most important uses of computer vision for solving a variety of problems. Due to the increasing demand for the security of welfare, security, and private property, the demands and implementation of security solutions that can recognise and analyse scene and anomalous occurrences play a crucial role in intelligent surveillance. Using convolution neural network (CNN)-based SSD and Faster RCNN techniques, this article develops automatic weapon (or) weapon detection. The implementation proposal employs 2 kinds of datasets. One dataset consists of pre-identified photos, whereas the other consists of manually labelled images. Results are tabulated, and both algorithms attain good accuracy; nonetheless, their implementation in real-world scenarios is contingent on a trade-off among speed and precision.

Index Terms— Computer vision, weapon detection, Faster RCNN, SSD, CCTV, Artificial Intelligence (AI)

I. INTRODUCTION

Weapons or Object tracking is the identifying of unexpected, unexpected, unexpected, and uncommon events or objects, which are not deemed to be a usually occurring activity or a normal element in a patterns or objects contained in a dataset, and are hence distinct from current patterns. A pattern that happens differently from a collection of standard patterns is an anomaly. Consequently, anomalies are contingent upon the phenomenon under study [3] [4]. Object detection employs extraction of features and learning techniques or models to identify occurrences of diverse object categories [6]. The performance of the proposed focuses on the accurate detection and classification of firearms. Also concerned with precision, as a false warning may result in negative outcomes [11] [12]. Choosing the best strategy necessitates a balance between precision and speed. Figure 1 depicts the deep learning process for weapon detection. The frames are derived from the video source. Before object detection, a frames differencing algorithm is implemented and a bounding box is generated [7] [8] [14].

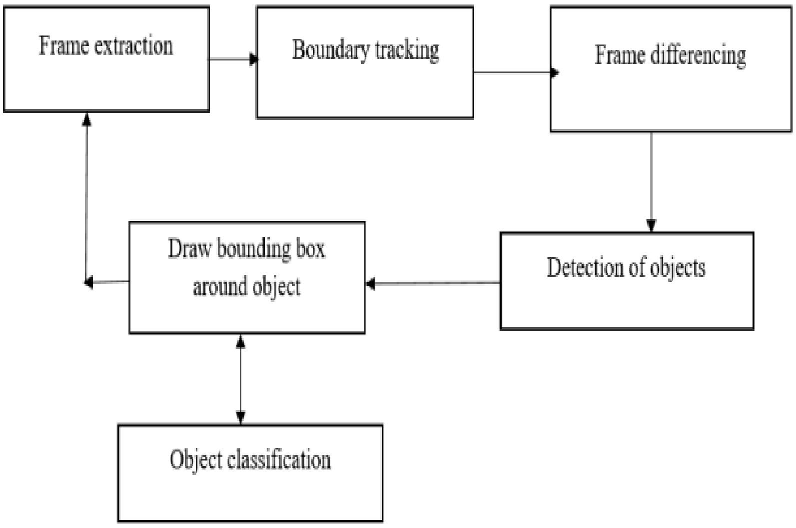


Fig.1.Methodology

The identification and tracking of objects as depicted in picture 2. The creation, training, and feeding of a dataset to an object detection algorithm. For gun detection, an application-appropriate detection method (SSD or fast RCNN) is selected. Using several machine-learning models, such as Region Convolutional Neural Network (RCNN) and Single Shot Detection (SSD), the method handles the detection problem [2][9][15].

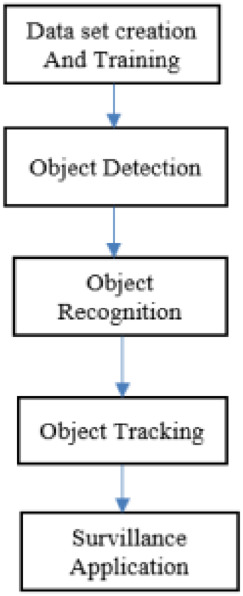


Fig.2. Detection and Tracking

II. RELATED WORK

The acronym SSD stands for Single Shot Multi-Box Detector

We offer a method that uses only a singular deep neural network to identify items present in visual data. Our method, which we have given the acronym SSD, takes the output matrix of bounding boxes and divides it up into a series of default boxes with varying dimensions and scales depending on where the feature map is located. [8] At the moment of prediction, the network creates scores for the existence of every object in the image in each default box. It also produces modifications to the box so that it more closely matches the shape of the object being predicted. Additionally, in order for the network to organically deal with objects of varying sizes, it mixes predictions from many feature maps that each have a varied resolution. When compared to methods in terms object proposals, SSD is straightforward because it does away with proposal generation entirely, as well as following pixel or characteristic resampling steps, and encapsulates all computing within a single network. This makes SSD easier to implement than conventional techniques object proposals. Because of this, SSD is simple to train and requires little effort to include into systems that call for a detection component. [1] The results of experiments performed on the PASCAL VOC, COCO, and ILSVRC datasets demonstrate that SSD has an accuracy that is comparable to that of methods that involve an additional object proposal step. Furthermore, SSD is significantly faster than those methods, and it offers a unified framework for the purposes of both training and inference. For a (300 'times 300') input, SSD scores 74.3 percent mAP on VOC2007 test at 59 FPS on an Nvidia Titan X, and for a (512 'times 512') input, SSD achieves 76.9 percent mAP, beating a corresponding advancements Faster R-CNN model. Both of these results were achieved on an Nvidia Titan X. SSD offers a significantly higher level of accuracy in comparison to other single-stage algorithms, even when the input image size is reduced. [10] The source code may be found at https://github.com/ weiliu89/ caffe/ tree/ ssd.

To detect large numbers of objects, Deep Neural Networks are used

On the ImageNet Large-Scale Visual Recognition Challenge, deep convolutional neural networks have recently outperformed all other competing systems (ILSVRC-2012). Localization was won by a network that predicted the location of a single structuring element and class probabilities for each image category. When numerous instances of an object are present in an image, a model like this would have to naively recalculate how many outputs each instance would require. [5] For detection, we present a sparsity neural network model in which each bounding box is assigned a score based on how likely it is to contain an object of interest. This model is class-agnostic. When it comes to cross-class generalisation, the model automatically manages a varying number of incidents for every class. A small number of artificial neural evaluations, [7] along with simply employing a tiny subset of the top indicated locations in each image, allow us to achieve excellent recognition accuracy on VOC2007 and ILSVRC2012.

An Analysis of Video Anomalies by Using Neural Networks for Video Surveillance

Because of an increase in crime rates at crowded events and in isolated, suspicious regions, safety is always a major worry in every field. Computer vision may be used to solve a wide range of issues by detecting and monitoring anomalies. [11] Video surveillance systems that can recognise and understand the scene and anomaly occurrences play an important role in data tracking because of the increased demand for safety, security, and personal property protection. Analyzing patterns and identifying outliers is the goal of anomaly detection. Videos taken by surveillance systems may reveal a wide range of plausible oddities. Visual based on the attached, image analysis, and activity detection are three components that make up detection techniques [3] in video surveillance systems. For video surveillance, detection system in videos provides reliable results in terms of real-time situations. The accuracy of this paper's detection of anomalies in photos and movies is 98.5 percent.

Research and Applications of AI in Data Science and Analytics: A Review of AI Methodologies

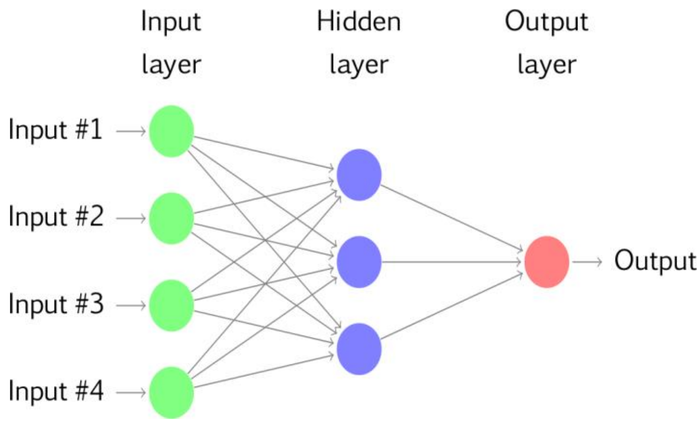
The ultimate goal of artificial intelligence is to automate any human activity that currently necessitates intelligence on the part of humans. Developing a system that operates like the human brain is the biggest challenge. Artificial intelligence's design approach must be reevaluated as part of its architecture. [4] Analytical approaches to resolving complicated problems are also popular in the field of data science. In this way, data can be broken down into smaller pieces and trends and behaviours can be identified. The primary challenge in computer science is dealing with massive volumes of data. There is a huge growth in research prospects, but a lack of computing capacity and human power remain major obstacles.

III. METHODOLOGY

To show how to construct a classification model using a convolutional neural network, we will construct a 6 layer neural net that can tell one image from another. This system we're planning on building is very short and can also run on a CPU. Recurrent neural networks that really are good at classifying images have a lot too many variables and take a long time to train on a regular CPU. But our goal is to show how to use TENSORFLOW to start building a new convolutional neural network.

Neural Networks are basically differential equations that are used to solve a problem with optimization. [15] Neurons are the basic unit of computation in neural networks. A neuron takes in a value (let's say x), does some math on it (let's say it multiplies it by a parameter w and keeps adding another parameter b), and then comes up with a value (let's say z = wx + b). This value is sent to a non-linear function is called activation function (f) to determine a neuron's final output, or "activation." Activation functions come in many different forms. Sigmoid is a popular way to turn on a function. Sigmoid neuron is the name for a neuron whose firing function is a sigmoid function [9]. Neurons are called things like RELU and TanH based on how they are activated. There are many different kinds of neurons.

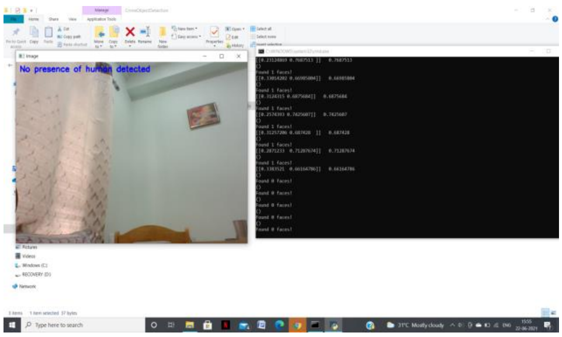
A layer is what you get when users stockpile neural connections in a single line. Layers would be the next basic foundation of neural networks. See the picture with layers below.



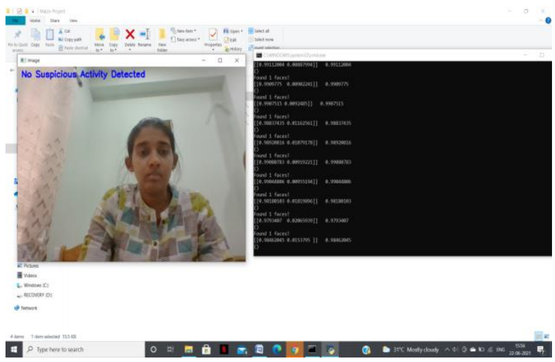
Various levels work together to find the highest rating layer, and so this procedure keeps going until there's no progress to be made.

IV. RESULT AND DISCUSSION

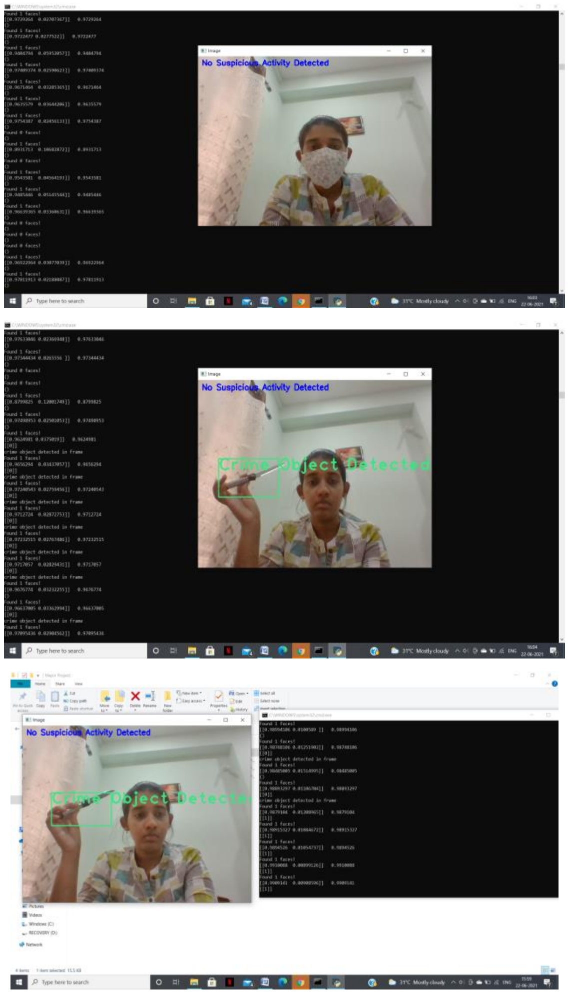
Run the project to get below result



There is no evidence of a human being in the results shown above



No suspicious activity was found in the above reports similarly shows below result



The criminal object can be seen in the aforementioned results.

V. CONCLUSION

Simulations of the SSD and Speed RCNN algorithms are performed on both a pre-labelled and a self-created image dataset in order to detect weapons (guns). Both of these algorithms are effective and produce quality outputs; however, the implementation of either of them in real time requires a compromise between speed and precision. When compared to other algorithms, the SSD algorithm provides superior speed at 0.736 seconds per frame. While Faster RCNN only achieves a speed of 1.606s/frame, which is significantly slower than SSD. In terms of accuracy, the Faster RCNN algorithm provides higher results, with an accuracy of 84.6 percent. But the accuracy provided by SSD is only 73.8 percent, which is subpar in comparison to that provided by RCNN, which is faster. Because of its greater speed, SSD was able to give real-time detection, but Faster RCNN delivered improved accuracy. In addition, it is possible to deploy it for bigger datasets by training with greater DSP and FPGA kits, as well as GPUs [6, 7].

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