REAL-WORLD ANOMALY DETECTION USING OBJECT RECOGNITION

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Abstract

Rising crime rates have increased the demand for surveillance cameras in all public places and streets. Our responsibility to curb criminal activity extends beyond the installation of surveillance cameras. Mechanisms are needed to provide immediate relief to victims of crime, along with immediate action against offenders. This can only be done through constant and careful monitoring of video policing, which ultimately requires human intervention. Therefore, the development of a real-time automated anomalous human activity detection system can be extended to multiple public locations specific to the application environment, such as schools, universities, airports, bus stops, hospitals and train stations that support specific needs. . Therefore, an accurate timing anomaly detection system is enhanced by sacrificing the intermediate results of adjusted video compression. The planned technology outperforms various existing systems in terms of accuracy and timeliness.

Keyword: - Machine Leaning, activity recognition, you only look once (YoLo-V3), computer vison.

I. Introduction

Human activity detection is being used more and more in public places. Detecting anomalies in security systems such as roads, intersections, banks, and search centers is one way to improve public security. Related activity recognition systems are expected to recognize basic daily activities performed by human presence. Due to the quality and diversity of human activity, it is difficult to achieve high accuracy for detecting that activity. It links to current and open analytical topics in computer vision, including examples of behavioral biometrics, video analytics, animation, and synthesis. Human behavior, including gestures and movements per physical structure domain, is understood with the help of sensors. The system understands an individual's activity by identifying movement and recognizing patterns in that movement. This is often followed by the development of complex conceptual abstract models that recognize and categorize all human activities. Furthermore, Activity Pattern Recognition does not require a defined model, as it simply uses the low-level device knowledge captured by the Area Unit to find unknown patterns. Although the two techniques are different from each other, they share a common goal of improving the recognition performance of action recognition systems. These techniques examine and combine each alternative to improve performance by inventing bullying activity patterns to outline perceived activity.

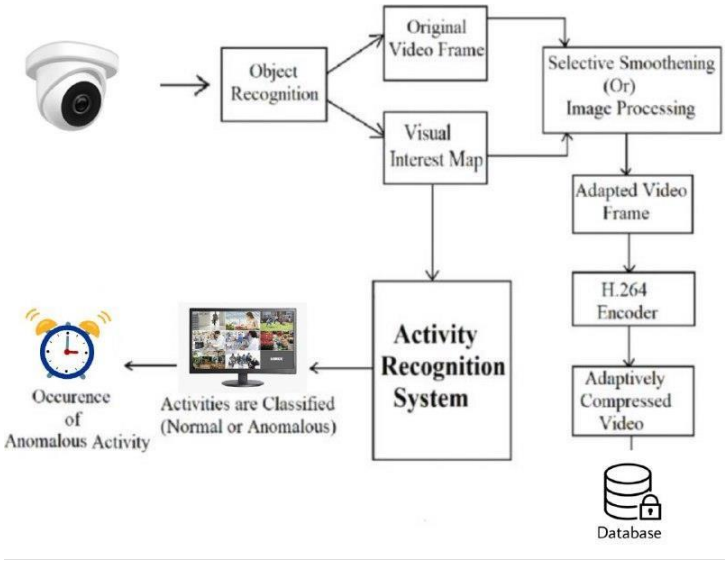

Fig.1 The high-level design of the anomalous human activity recognition system

II. Adaptive Video Compression

There are a number of approaches that Area Unit has taken to video compression, some of which simply reduce video scaling and compress the entire video. Some useful information is lost when such an approach takes root in a unit. Therefore, it is appropriate to use many cheap compression techniques to ensure that no important information is lost from the video. In other words, adaptive video compression compresses the non-essential elements of the video and preserves the elements that contain the target object of interest. General video compression is controlled. Here, the important and semantically meaningful parts of the video area unit are encoded with higher precision. This can be achieved by combining low-level video options with low-cost machines. Insignificant background components are assigned the lower bits in the transmitted representation. The idea of this method is to smooth individual frames by selection, as shown in Figure 1. Selective smoothing is therefore useful for protective image options for objects that look semantically interesting, i.e. personality movements in the case of human activity detection. Every single frame of video is adaptively compressed using a low-level function to eliminate uninteresting elements. This result is used for the preprocessing status that is inserted into the video encoding pipeline. Therefore, adaptive compression techniques first identify the target object and then perform selective smoothing whenever unimportant elements of the unit image region are resolved. The insignificant elements of surveillance video mostly form the background as they always remain constant. Therefore, once a movement is known, it can be considered to recognize and classify it. For each movement of a person, the corresponding person is recorded as an object. This object is tracked to see what activity is running.

III. Anomaly Detection

Human activity can be broadly divided into normal activity and abnormal activity. Individual deviations from normal behavior that harm the environment or themselves are classified as abnormal activity. Such behavior may be the result of psychological discomfort. Intensive inspection of anomaly detection is realized by human behavior detection and its application. Current approaches for detecting abnormal human behavior are aided by the nature and speed of motion of objects of interest as they interact with each other. A survey of different approaches on the market has revealed the shortcomings of existing activity detection systems. This is the main motivation for implementing an automatic anomaly detection system that works in real time. OpenCV, scikit-learn, is a set of libraries used to implement a periodic anomaly detection system together with YOLOv3 (You Only Look Once, version 3).

IV. LITERATURE SURVEY

Real-world Anomaly Detection in Surveillance Videos filters by: - Waqas

Sultani, Chen Chen, Mubarak Shah

This paper was 14 Feb 2019.They planned a technique to find out anomalies by exploiting each traditional and abnormal video. They additionally think about traditional and abnormal videos as baggage and video segments as instances in multiple instance learning (MIL), and mechanically learn a deep anomaly ranking model that predicts high anomaly scores for abnormal video segments. The algorithmic rule and technology utilized by them are Multiple Instance Learning.

Anomaly Detection in Video Sequence with Appearance-Motion Correspondence filters by Trong Nguyen Nguyen, Jean Meunier

This paper was revised on 17 Aug 2019.The given paper proposed a deep convolutional neural network that addresses the downside of anomaly detection in surveillance by learning a correspondence between common object appearances (e.g., pedestrian, tree, etc.) and their associated emotions. The algorithmic rule and technology utilized by them are a convolutional neural network (CNN).

Deep anomaly detection through visual attention in surveillance videosfilters by: - Nasaruddin Nasaruddin, Kahlil Muchtar, Afdhal Afdhal & Alvin Prayuda Juniarta Dwiyantoro.

This paper was published on 16 October 2020.This paper used a technique for learning anomaly behavior within the video by finding an attention region from spatiotemporal information, in distinction to the full-frame learning. They additionally used a similar algorithmic rule and technology utilized by them is a convolutional neural network (CNN).

Video anomaly detection method based on future frame prediction and attention mechanism filters by: Chenxu Wang, Yanxin Yao , Han Yao.

This paper was published on 17 March 2021.The given paper proposes a video anomaly detection algorithm based on the future frame prediction using Generative Adversarial Network (GAN) and attention mechanism. Limitations and technical gap of this paper is that this paper needs to provide different types of data continuously to check if it works accurately or not.

Activity recognition and anomaly detection in smart homes filters by: Labiba Gillani Fahad, Syed Fahad Tahir.

This paper was revised on 12 November 2020.They planned the approach that acknowledges the activities performed in a very sensible home and separates the conventional from the abnormal activities. The algorithmic rule and technology utilized by them is water autoencoder.

Contextual Multi-Scale Region Convolutional 3D Network for Activity Detection by: Yancheng Bai, Huijuan Xu, Kate Saenko, Bernard Ghanem.

This paper was published on 28 January 2018. They proposed the contextual multi-scale region convolutional 3D network (CMSRC3D) for activity detection. Limitations and technical gap from this paper is that it complicates the vision-based detection systems and the issue of objects appearing in images with different pixel-wise.

Anomalies Detection and Tracking Using Siamese Neural Networks by: Yan, Weiqi

This paper was published on 15 May 2020. The proposed model is based on the single-target tracking network Siamese-RPN, which assists multi-target tracking through a cyclic structure. Limitations and technical gap from

this paper is that the distribution of training samples is imbalanced, positive samples are far less than negative samples, leading to ineffective training of the Siamese network.

Machine Learning for Anomaly Detection: A Systematic Review

By: Ali Bou Nassif, Manar Abu Talib Qassim Nasir Fatima Mohamad Dakalbab.

This paper was revised on 25 May 2021.The given paper conducted a Systematic Literature Review (SLR) which analyses ML models that detect anomalies in their application. Limitations and technical gap from this paper is that an SLR's quality depends on what has been published in the literature.

Real-Time Anomaly Recognition Through CCTV Using Neural Networks

By: Virender Singha, Swati Singha, Dr. Pooja Guptaa.

This paper was published on 1 July 2020. The given paper proposed an idea to reduce the wastage of time and labour, they are utilizing deep learning algorithms for Automating Threat Recognition System. Limitations and technical gap from this paper is that it is difficult to detect small objects along with that it only predicts a label, not a segmentation box.

Anomaly Event Detection in Security Surveillance Using Two-Stream Based Model by: Wangli Hao,1 Ruixian Zhang,1 Shancang Li,2 Junyu Li,1 Fuzhong Li ,1 Shanshan Zhao,2 and Wuping Zhang1.

This paper was revised on 03 Aug 2020. The paper proposed a novel two-stream convolutional networks model for anomaly detection in surveillance videos. The algorithm used in the given paper is RGB and Flow two-stream networks. Limitations and technical gap from this paper is that it is non-useful for object specification and recognition of colors along with that it is difficult to determine a specific colour.

Proposed Methodology

Recent surveillance cameras can record the video if motion is detected but in old surveillance cameras continuously records the video regardless of motion detected. This will improve system efficiency by reducing processing, searching time and storage required to save the recorded videos. The protective services and authorities often fail to respond efficiently in crime incidents, because they follow reactive approach. In reactive

approach authorities depends on witness report or closed-circuit television (CCTV) footage for analysing about the crime after it had occurred. In most of the cases when an incident was occurred, investigators visit the site of the incident, manually retrieve the footage from camera, and then try to locate the appropriate footage either by watching the full length of the video or by Processing it by using advanced algorithms. An efficient crime prediction analysis system for smart home is required to enable the robust security management, thus minimizing the crime incidents and losses. In this paper a framework for real time crime analysis and prediction in smart home using webcam is implemented. This framework has three main steps they are:

- Intelligent Motion detection
- Object detection
- Face recognition

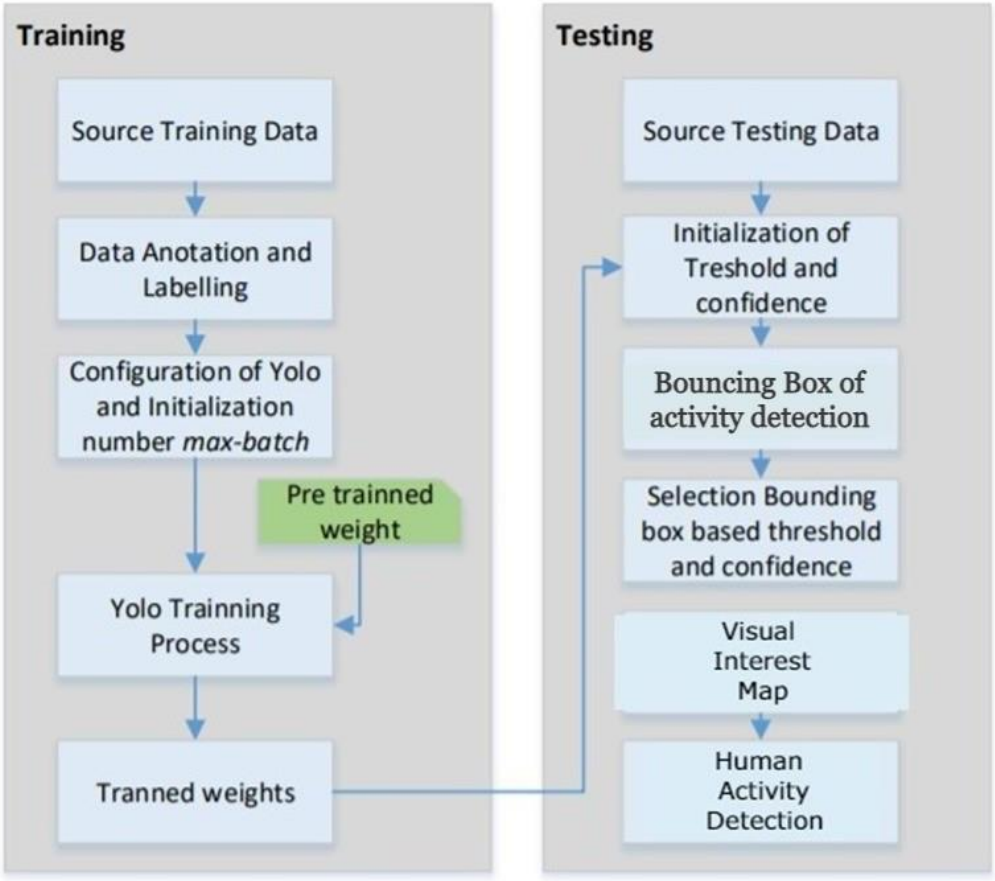

Fig.2 Proposed Method

	backbone	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Two-stage methods							
Faster R-CNN+++	ResNet-101-C4	34.9	55.7	37.4	15.6	38.7	50.9
Faster R-CNN w FPN	ResNet-101-FPN	36.2	59.1	39.0	18.2	39.0	48.2
Faster R-CNN by G-RMI	Inception-ResNet-v2	34.7	55.5	36.7	13.5	38.1	52.0
Faster R-CNN w TDM	Inception-ResNet-v2-TDM	36.8	57.7	39.2	16.2	39.8	**52.1**
One-stage methods							
YOLOv2	DarkNet-19	21.6	44.0	19.2	5.0	22.4	35.5
SSD513	ResNet-101-SSD	31.2	50.4	33.3	10.2	34.5	49.8
DSSD513	ResNet-101-DSSD	33.2	53.3	35.2	13.0	35.4	51.1
RetinaNet	ResNet-101-FPN	39.1	59.1	42.3	21.8	42.7	50.2
RetinaNet	ResNeXt-101-FPN	**40.8**	**61.1**	**44.1**	**24.1**	**44.2**	51.2
YOLOv3 608×608	Darknet-53	33.0	57.9	34.4	18.3	35.4	41.9

V. High-Level Design of the Model

The system design of the planned model shown in Fig. one describes that the videos captured from the p surveillance cameras are reborn into frames for visual perception. Once the target object is known, a visible interest map is generated, that is employed to coach the activity recognition system. at the same time, the framesare by selection ironed leading to adaptive compression. Thus, the associate degree intermediate step of adaptivevideo compression is pipelined into the activity recognition system aspiring to enhance the system's performance.

VI. Model Detection

YOLOv3 has wonderful detection effects within the field of object detection. YOLO algorithmic program improves the speed of detection as a result of it will predict objects in a period of time. YOLO may be a predictive technique that has correct results with the minimal background errors. The algorithmic program has wonderful learning capabilities that alter it to find out the representations of objects and apply them in object detection.

Motion detection is the mechanism by which a change in the location of an object relative to its background or a change in the background relative to an object is detected. The key applications of motion detection are the detection of unauthorized entry and the detection of a moving object that allows a camera to record subsequent events. A simple motion detection algorithm compares the current image to a reference image and simply counts the number of different pixels. Due to factors such as changing lighting, camera flicker, and CCD dark currents, images will naturally differ, pre-processing is useful to minimize the number of false positive output. For detecting the moving objects in video, background subtraction model is used.

VII. Face Detection

If motion is detected, then next step is to detect face in live stream. Face detection is performed by using Haar feature based cascade classifier which is an effective detector of objects. It is an approach based on machine learning. Lot of Positive and negative images are used to train the cascade function, then it is used for comparing with other images for object detection. There are huge individual XML files with lot of features, each xml files have a specific use case feature. Here for face detection, haarcascade_frontalface_default.xml is used which has features for detecting the front face. This xml has values which is obtained when training with lot of positive and negative images for detecting the front face. Face detection model is designed using OpenCV which is most familiar way to detect the face.

VIII. Implementing Object Detection using YOLOv3

We have used YOLOv3 to implement the object recognition & the algorithm automatically identifies the category of interest and their individual Anchor box and maintains a counter. we've got used the pre-trained YOLOV3 model, which is capable of detecting “person” as a category, and that we count the number of individuals by maintaining a counter. Time period video frames had given as input to our model & our model detected the anomaly counter.

Fig.4: Anchor Box Detection

IX. Object detection and Recognition

Object Recognition is one of the computer vision techniques for identifying instances of objects in images or videos. The primary objective of object detection is to replicate the human intelligence of detecting object in a video or image to computers. The use cases of object detection are infinite some of them are monitoring objects, video surveillance, pedestrian identification, identification of anomalies, people counting, self-driving cars or face detection and so on. Object detection model is designed based on YOLOV3 and Darknet for custom data. Custom

data here considered are Knife and Gun. Following are procedures involved in designing the object detection model are:

1. Set up YOLO V3 on windows. Install all dependencies they are Visual Studio 2019, CUDA>=10.0, cuDNN>=7.0, CMake>=3.12, OpenCV>=2.4. Ensure to add OpenCV, CUDA, cuDNN directory in environmental variables. Then clone the darknet directory from https://github.com/AlexeyAB/darknet. Set up the config file with the CUDA version installed cuDNN directory in environmental variables. Then clone the darknet directory from https://github.com/AlexeyAB/darknet. Set up the config file with the CUDA version installed and then build the solution using visual studio 2019 which will generate darknet.exe file. Copy cuDNN64_7.dll, OpenCV ffmpeg420_64.dll, OpenCV_world420.dll file to darknet bin folder.

2. Using Image annotation tool Labelimg which is a powerful tool used for image annotation and labelling. Using this tool labelImg and annotation and labelling is done and save the file generated for each custom image in txt file which contains annotation and labelled values for each image. Define class file which has names of the objects that should be detected.

3. Prepare config file for custom data by modifying the yolo config file in darknet. Create object name folder for training and object data folder which has train data path, validation data path, classes, names of custom object file and path for storing the trained data. Download pre trained CNN weights for YOLO.

4. Train using darknet for custom data using pre trained weights.

5. Using an object detector model coded using yolo v3 and OpenCV for detect the objects in real time which is able to detect the knife and gun.

Once the image frames have been loaded, parameters for nms_thresh and iou_thresh, we are able to use the YOLO algorithmic program to discover objects within the image. We tend to discover the objects using the detect_objects(m, resized_image, iou_thresh, nms_thresh)function from the utils module. This function takes in the model to come to the resized image, and therefore the NMS and IOU thresholds, and returns the Anchor boxes of the objects found.

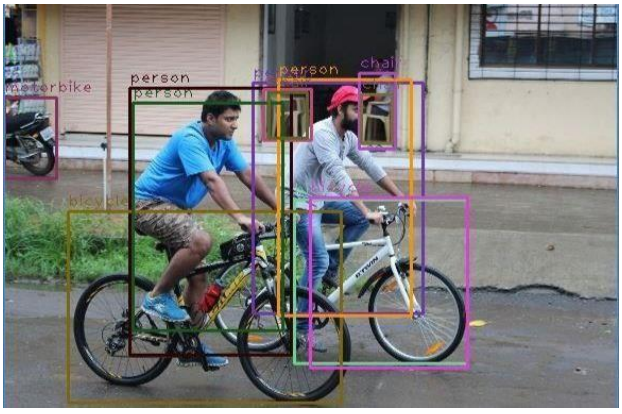

Fig5. Object Detection

X. Input Image Processing

The output is obtained by running the input image through a CNN network, which consists of Convolution and Detection layers sequentially. In this instance, the input image is divided into 19*19 grid cells, with 5 predetermined anchor boxes for each grid cell. This gives us a total of 1805, with 85 predicted elements from the network being the output for each anchor box.

XI. Face Recognition

The next step after object detection is face recognition. Face recognition model is built using a Face recognition function defined by adam geitgey. Face recognition package is downloaded using pip command. Then built a model to recognize the face in real time. Humans are capable to identify the person easily and quickly, but computers cannot. In order to make computers to do that following procedures are involved they are: find face in image, analyze facial features, compare against known face and then prediction. The first step is finding the face which involves, convert the RGB image to gray image then divide the image into 16*16 pixel each. For each pixel calculate the gradients point in each major direction replace that square in the image with the arrow directions that were the strongest. Using HOG Face is detected for given image. Face landmark estimation algorithm is used for locating the 68 face landmarks on given image, condition is that eyes and nose should be visible in image. A pre trained convolution neural Network "Open Face" is used to generate 128 measurements for each face. By calculating the Euclidean distance between the image encodings, comparing the distance face prediction is performed.

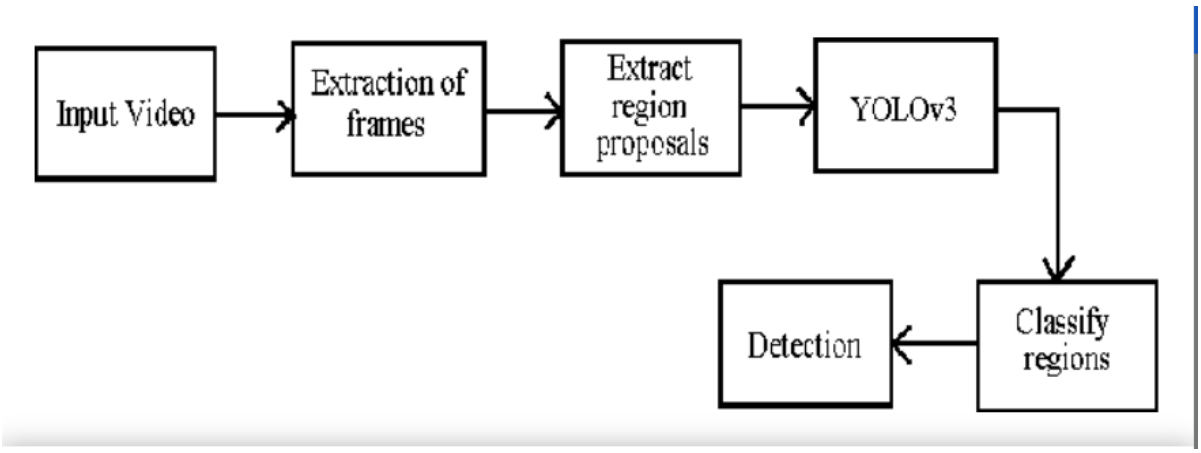

Fig.6 Basic block diagram of suspicious activity detection.

XII. Project Architecture

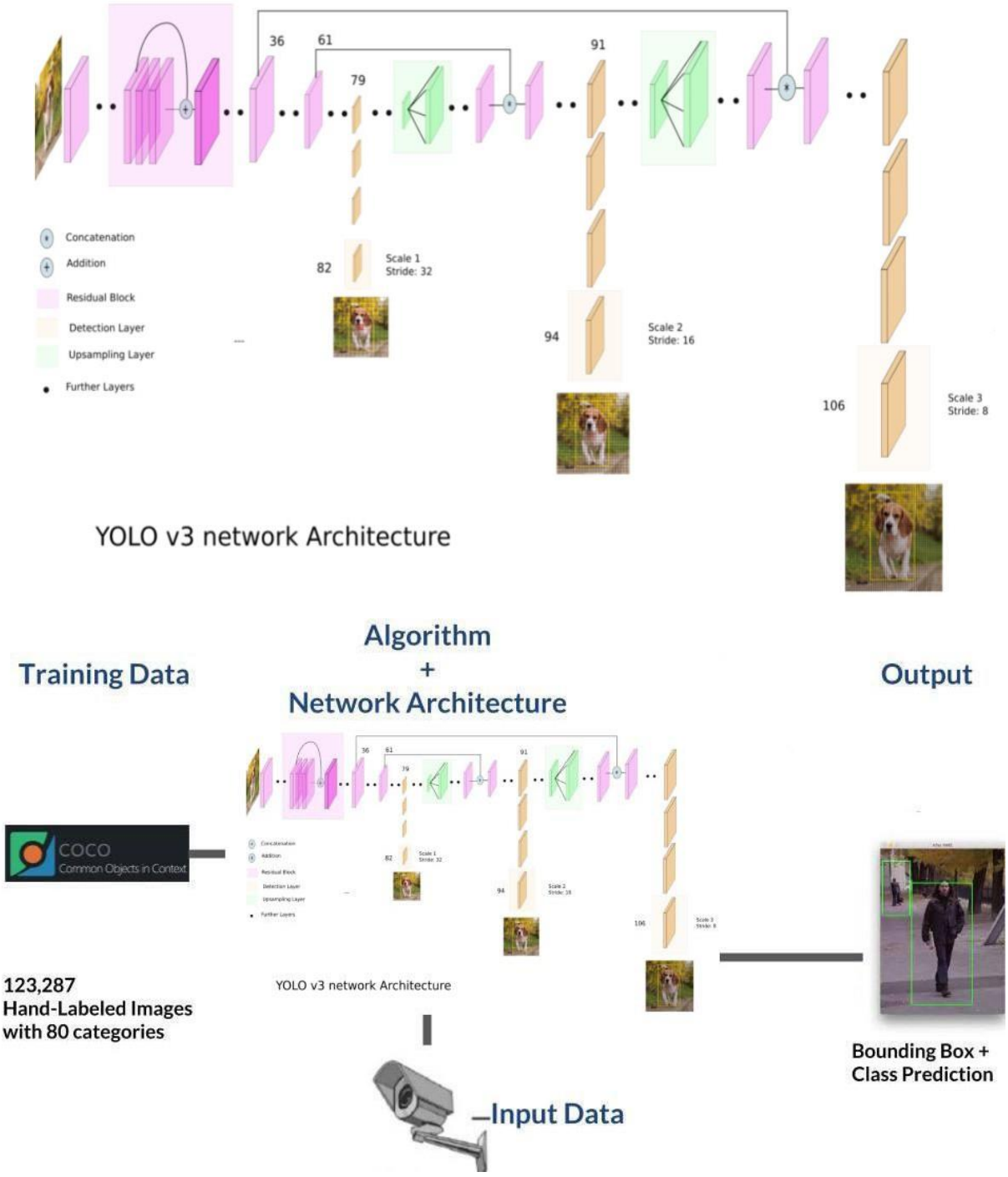

Fig.7 YOLO v3 Network Architecture.

XIII. EXPERIMENTATION AND RESULTS

A. Implementation Details

We use YOLOv3 to implement object recognition and the algorithm automatically identifies the desired class and anchor box respectively and maintains a counter. We use the pre-trained YOLOV3 model, which is capable of detecting "people" as a class and we count the number of people by creating a counter. Real-time video frames have been provided as input to our model, and our model detects an anomaly counter.

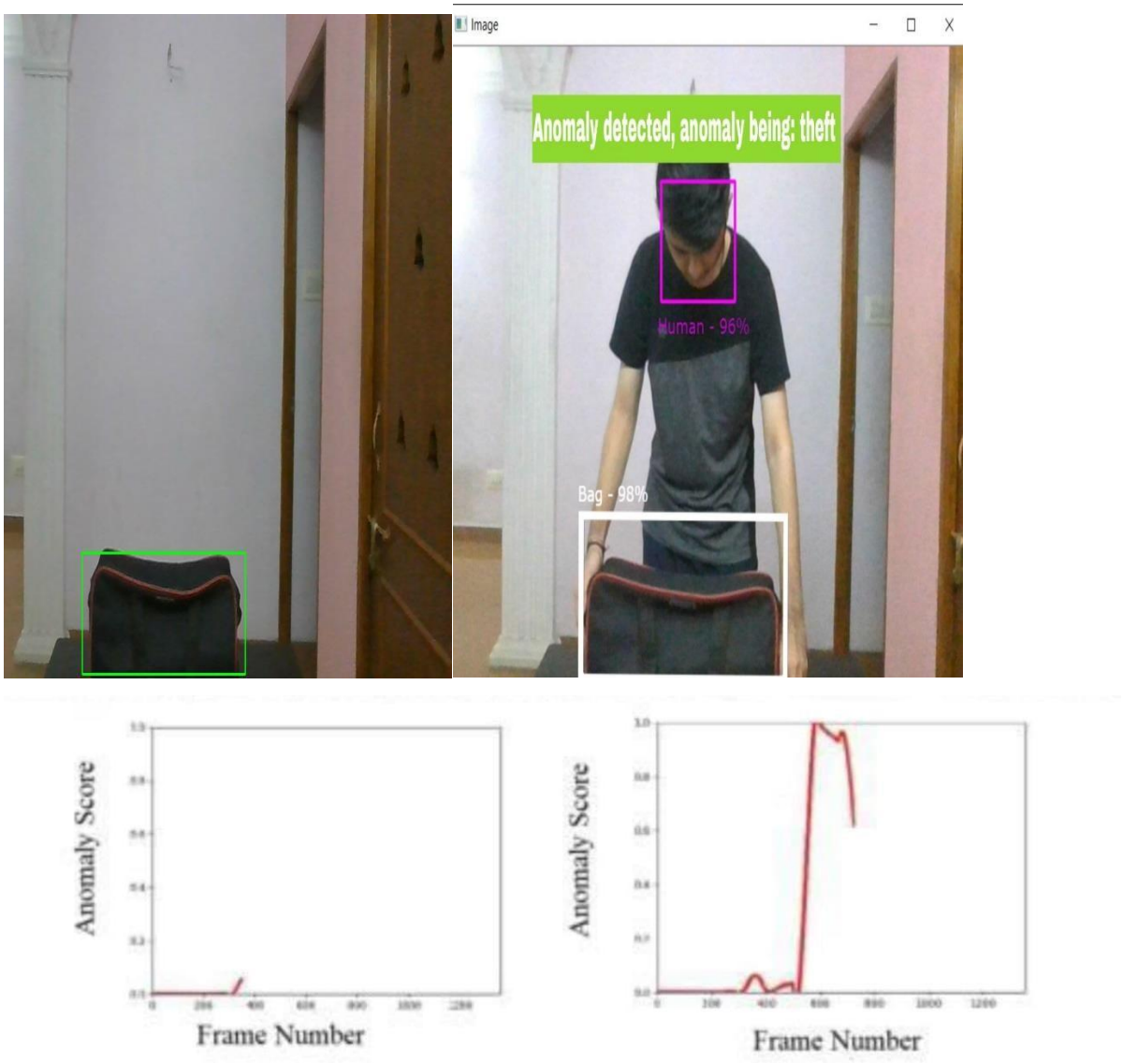

Fig.8: Anomaly detected, anomaly being: theft

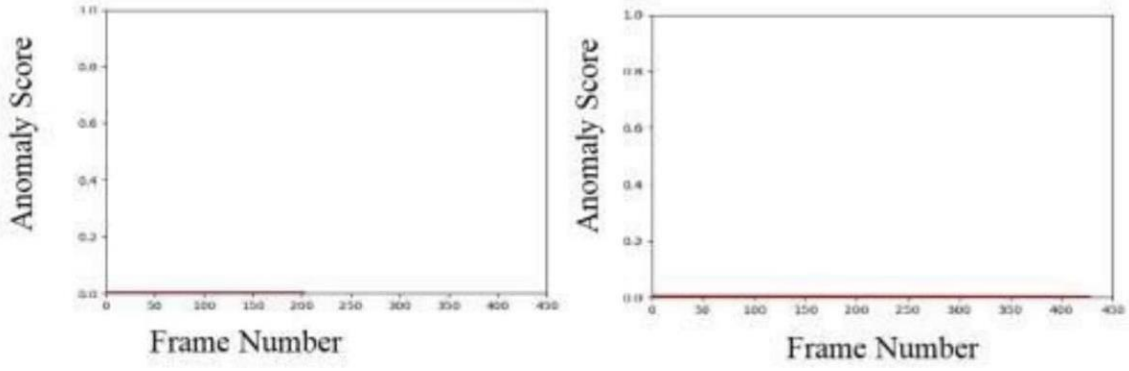

Fig.9: Test result for a video with no anomaly

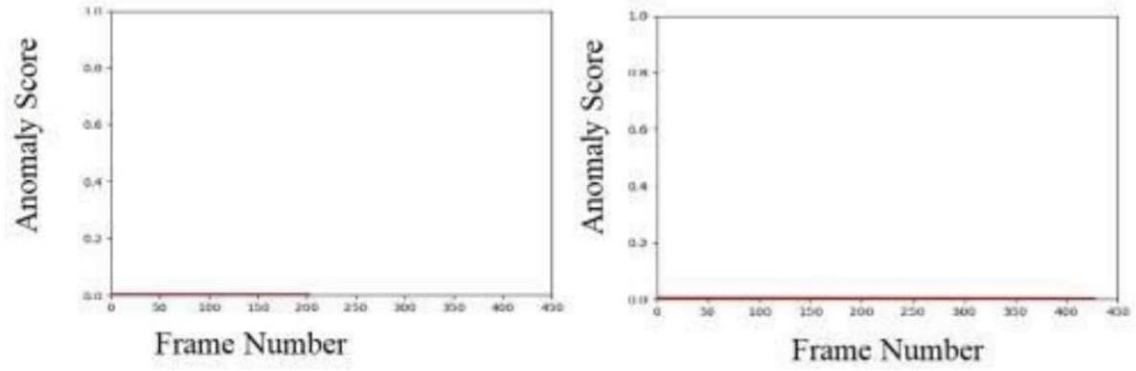

Fig.10: Test result for a video with no anomaly

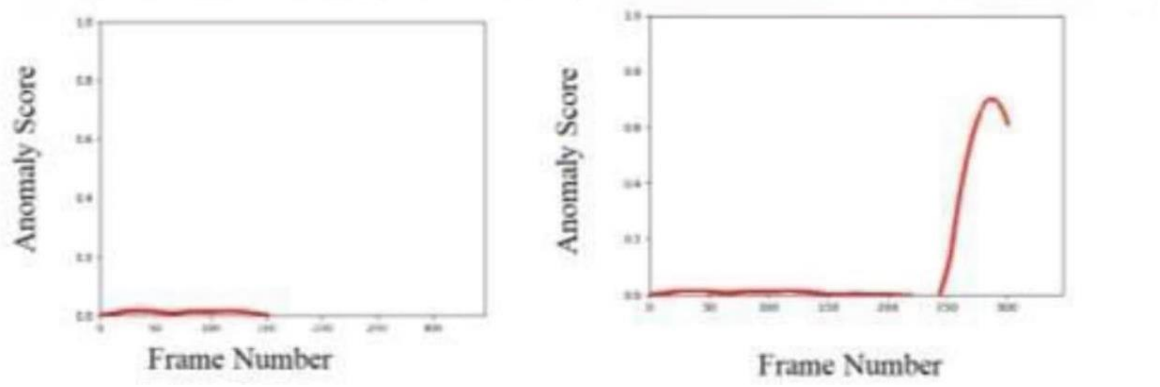

Fig11.: Anomaly detected, anomaly being theft

B. Pre-Processing Data

Suppose this detection system is installed in the house so first, we will scan the house owner's face then our model will get trained on the faces it collected after this our detection system will start video stream this stream will act as input to our model. When any person comes near to the system it will run a similarity check with the face in the input stream and the trained faces, if the similarity accuracy is greater than 85-90 percent then our model will keep on running and if the similarity is less than 80 percent the model will start the lockdown procedure in which alarms will on and the registered members will get triggered.

C. Comparison With Other Model

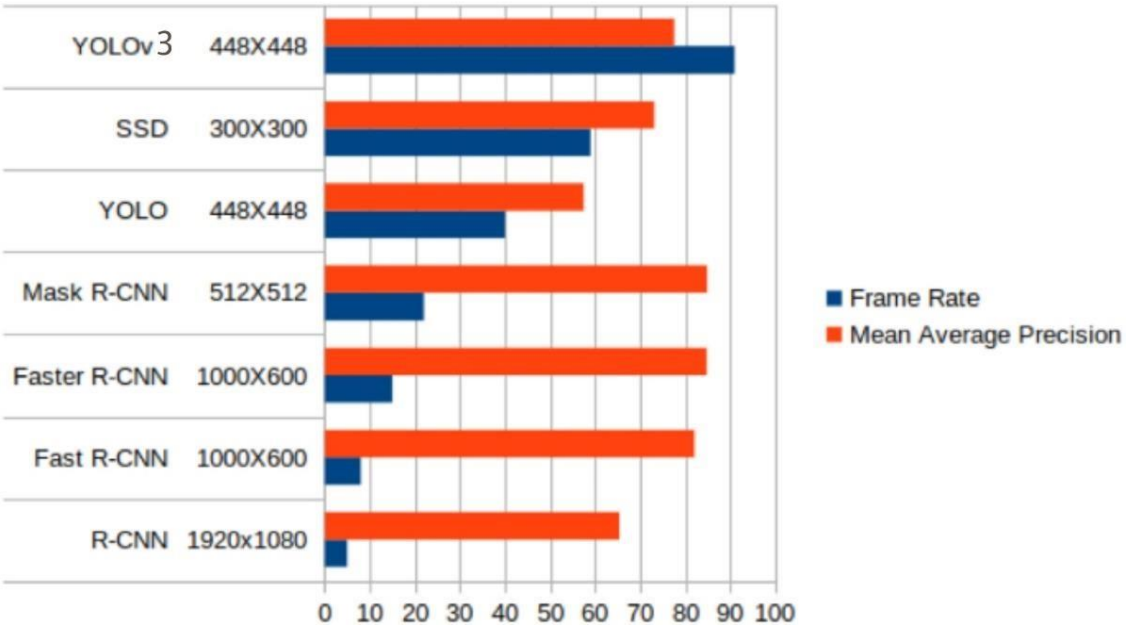

Fig.12.: Anomaly detected, anomaly being theft

Prior detection systems repurpose classifiers or localizers to perform detection. They apply the model to a picture at multiple locations and scales. High grading regions of the image are thought of as detections. We use a completely totally different approach. we have a tendency to apply one neural network to the total image. This network divides the image into regions and predicts bounding boxes and chances for every region. These bounding boxes are weighted by the expected changes. Our model has many benefits over classifier-based systems. It looks at the whole image at test time so its predictions are informed by global context in the image. It conjointly makes predictions with one network evaluation, not like systems like R-CNN that need thousands for one image. This makes it extraordinarily quick, quite 1000x quicker than R-CNN and 100x quicker than quick R-CNN. See our paper for additional details on the total system.

D. False alarm rate

In real-world Anomaly Detection, A robust anomaly detection should have a low false alarm rates as compared to normal situation. Therefore, we evaluate the performance of our approach and the other normal methods then false alarm rates of different approaches at 50% threshold. Our approach has a much lower false alarm rate than other methods, indicating a more robust anomaly detection system.

E. Accuracy

The accuracy of the YOLO algorithm, there are 2 accuracy calculations, namely Detection Accuracy (% DO) and Recognition Accuracy (% TL). Detection accuracy is the value of how accurate the YOLO algorithm is in detecting a object. This accuracy can be searched by looking at how accurate the YOLO algorithm is in making boxes of all objects in the image/video. Recognition accuracy is the value of how accurate the YOLO algorithm is in recognizing a object. This accuracy can be searched by looking at how accurate the YOLO algorithm is in giving the right labels and according to the type of object.The detection accuracy and recognition accuracy formula are:

$Detection\ Accuracy$ (%DO) = $Number\ of\ objects\ detected\ Total\ number\ of\ objects$ ∗100 (%) (1)

$Recognition\ Accuracy$ (%TL) = $The\ number\ of\ correct\ labels\ Total\ number\ of\ labels$ ∗100 (%) (2)

The calculation of accuracy is divided into two, namely calculating accuracy based on the recognized human beings and the calculation of accuracy based on their anomalous Activities. We have been carried out with data without pre-processing; the accuracy obtained is shown

in Table

Table: Accuracy of a dataset with pre-processing.

Dataset with pre-processing	Detection Accuracy (% DO)	Recognition Accuracy (% TL)
Without distraction	98.2	88
Brightness (+25)	97.6	88

Brightness (+50)	95.9	80
Brightness (+75)	94.1	86
Brightness (-25)	98.2	88
Brightness (-50)	97.7	84
Brightness (-75)	97.0	84

XIV. Conclusion and Future Work

Rising crime rates have increased the demand for surveillance cameras in all public places and streets. Our responsibility to curb criminal activity extends beyond the installation of surveillance cameras. Mechanisms are needed to provide immediate relief to victims of crime, along with immediate action against offenders. This can only be done through constant and careful monitoring of video policing, which ultimately requires human intervention. Therefore, the development of a real-time automated anomalous human activity detection system can be extended to multiple public locations specific to the application environment, such as schools, universities, airports, bus stops, hospitals and train stations that support specific needs. . Therefore, an accurate timing anomaly detection system is enhanced by sacrificing the intermediate results of adjusted video compression. The planned technology outperforms various existing systems in terms of accuracy and timeliness.

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