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Pseudo Trained YOLO R_CNN Model for Weapon Detection with a Real-Time Kaggle Dataset

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Abstract: The Recurrent Convolutional Neural Networks (RCNN) based deep learning models has been classified image patterns and deep features through layer architecture. In this world every country doesn't encouraging violence, so that indirectly nations prohibiting usages of weapons to common people. This study proposes a novel YoLo Faster R-CNN based weapon detection algorithm for unusual weapon object detection. The proposed YoLo V3 R-CNN computer vision application can rapidly find weapons carried by people and highlighted through bounding-box-intimation. The work plan of this research is divided into two stages, at 1st stage pre-processing has been called to Faster R-CNN segmentation. The 2nd stage has been training the dataset as well as extracting 8-features (image_id, detection score, pixels-intensity, resolution, Aspect-ratio, PSNR, CC, SSIM) into .csv file. The labeling can be performed to RCNN-YoLo method such that getting real-time objects detection (Unusual things). The Confusion matrix has been generating performance measures in terms of accuracy 97.12%, SSIM 0.99, sensitivity 97.23%, and throughput 94.23% had been attained which are outperformance methodology.

Keywords: Object detection, surveillance, computer vision, deep learning, YOLO, R-CNN

1. Introduction

Image processing is an analysis performed on hidden features and get deep infromation which is loaded to .csv file. It is similar to signal processing techniques where the input is considered as image and output has been reconstructed as highlighted unusual object. The following functionality has been taken over from many earlier research methodologies and Engineering models but those are outdated. Therefore, an advanced image

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processing technology has been required for medicine, remote sensing and etc. applications. Generally, image is considered as two continuous variables x and y. The pre-processing has been initially extracted features and digitally sampled by using transformed matrix. The precision can be measured from statistical analysis on training dataset. Images are processed in a number of ways, including image enhancement, image restoration, image analysis, and image compression. The 2 types of image processing technologies noting but Digital Image Processing and Analog Image Processing.

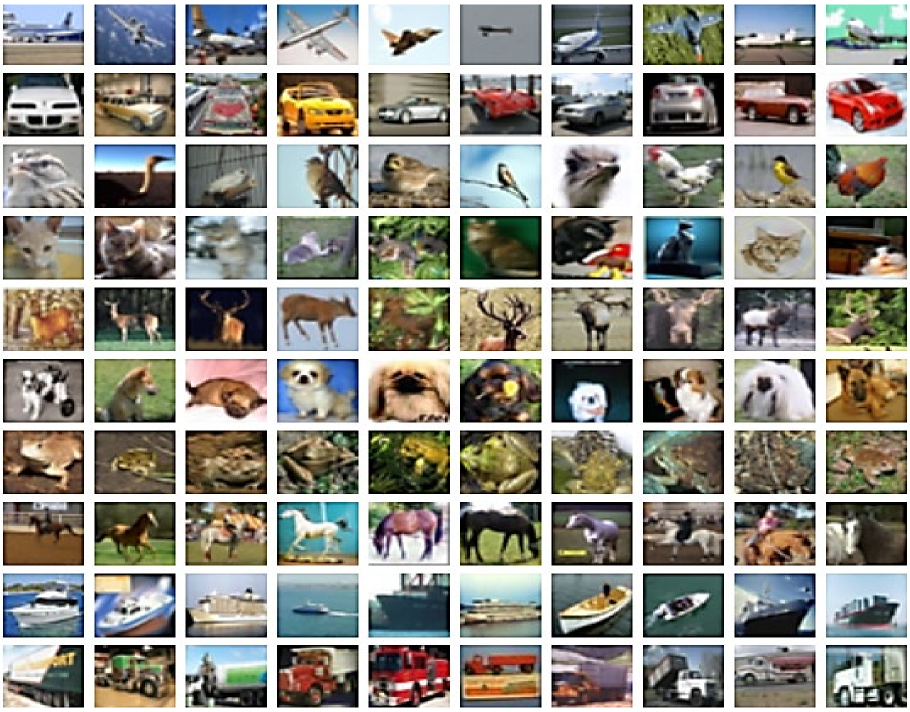

Fig. 1 - CIFAR-10 dataset (open source)

The algorithms related to digital image processing are challenges to recent pattern recognition applications, the build-up and distortion noise factors mostly effected to analog image applications. Therefore, digital image processing technologies are come to picture. The wide range of applications like agriculture, medical, health, industry and military sectors has been used image processing in various pattern recognition steps. The discrete mathematical theory is supporting image editing tools in efficiency way. The violence causes mass disturbance and huge loss for the individuals i.e., for civilians. Most recent is attacks which took places in many countries in the world, where the bombed vehicle rammed into the military convoy which was a huge disaster killing many militants. To overcome this, the real time weapon detection integrated to surveillance camera technology is required. The image processing methods can detect the vehicles passing by the roads and tunnels through checkpoints. The latest object detection model YOLO v3 is used along with RCNN. The Object detection has gained recognition in the recent days due to its research outbreaks and contribution to the society for real time applications. The computer vision field has incorporated the deep learning model which includes the general object detection and domain specific object detection. object detection is a computer vision and image processing technique that deals with the detection of objects in an image or video. This is very much similar to the latest process of detecting people in public places whether they are wearing a mask or not. In this paper section 1 briefly explains about latest image processing methods related proposed methodology. The section 2 is concentrated on literature survey pointing to limitations of existed methods. Section 3 is illustrating novel implementation YoLo v3 RCNN methodology. The section 4 and 5 consist of experimental results and conclusions of proposed study respectively.

2. Related Methods

The existing object detection models are involving in digital image processing which are used to enhancing image quality, brightness, color etc. based on the HSV (hue, saturation, value). The setting and adjustments have been performed according to particular image processing tools [1][2]. Some image processing applications cannot be useful for real time surveillance these methods have been failed and they use only for stable detection process i.e. for checking in airports, railway stations, forensics etc. Initially object detection was based on template matching techniques and part-based models [3][4]. Later detection was based on statistical classifiers (Neural Networks, RFO, CNN, SVM etc). But the initial techniques perform the task within the allotted scale and size whether object is there or not for this prediction is made. At that time three methods were in practice first method is based on bag of words where it verifies the presence of object and efficiently identify the region in an image [5][6]. Second method searches for the regions of image wherever the object is present. In third method it finds the key points and matches them to perform detection. Using these methods there is no assurance that the object instances are always detected [7][8].

Table 1 - Literature survey

S No	Technique	Accuracy (%)	Detection score (%)	Limitations
1	Adaptive beam forming using micro wave frequencies [9]	63.23	54.92	The reconstruction is much complex compared to all other image processing techniques
2	The computerized machine learning based liver abnormalities detection [10]	64.53	65.28	The classification and feature extraction process is difficult compared to
3	An infrared Monitorization for object detection [11]	67.32	68.93	Feature of objects are mis-classified and corresponding image haven't been estimated
4	Higher order differential equations [12]	69.24	70.23	Conventional models are most prominent and extracting hidden feature but design implementation is more economy
5	Feature fusion and deep learning technology [13]	71.34	72.54	The feature fusion technology is much better compared to ML and DL but maintenance of application is complex
6	Robust video processing system for object detection [14]	69.45	68.28	Object detection is considerable multifaceted with SVD hybridization technology
7	An IoT based home auto-machine technology [15]	73.27	75.67	In this work with machine and deep learning technologies has been used so that hidden samples analysis cannot be done.
8	Health care monitoring using sensor data [16]	75.34	78.92	The sensor data has been used to train the model and getting hidden information.
9	IoT based weapon objects detection [17]	79.82	81.24	YoLo V4 based object detection model facing target reconstruction issues.

10	Raspberry pi based real time violence detection [18]	82.34	89.93	This method is facing mis-classification issues at object detection

The above table 1 briefly explains about a deep discussion of object detection model for unusual events, in this existed model have been facing many deign issues and performance issues [19][20]. The limitations of deep study have been discussed with proper examples [21][22].

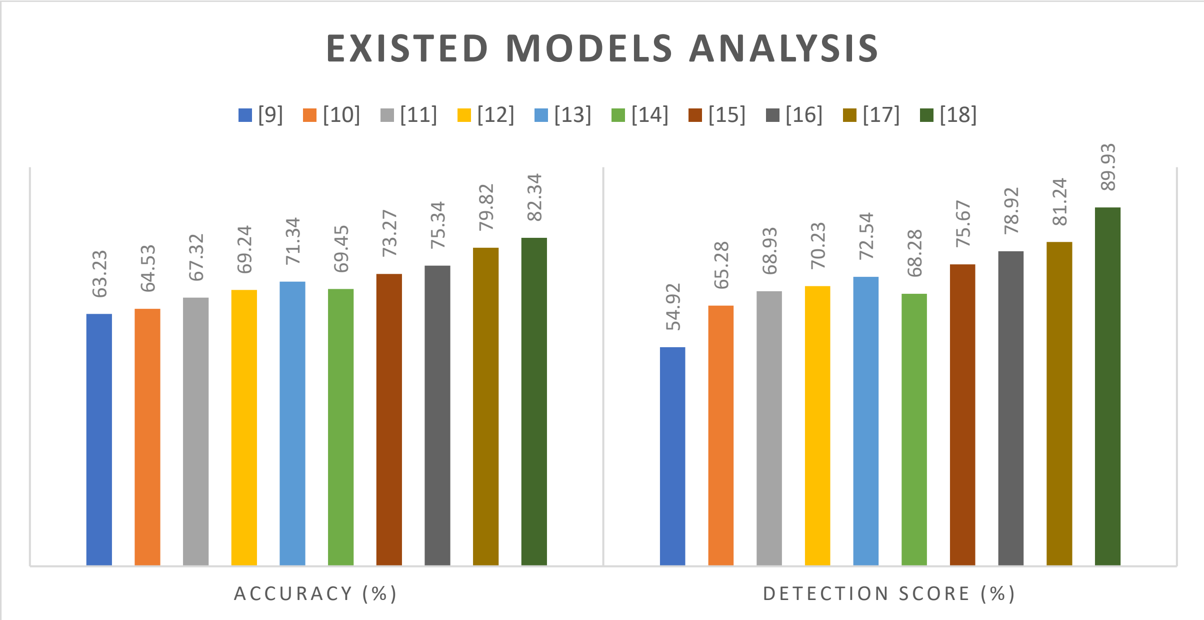

Fig. 2 - Various object detection models analysis

The figure 2 briefly explains about various object detection models and its limitation, moreover performance measures has been differentiated terms of accuracy as well as detection score [23][24]. The below section is concentrating on proposed methodology, in this design aspects are followed with esteemed to R-CNN YoLo V3 technique [25].

3. Proposed System

In this section a brief note on YoLo V3 modeling with RCNN deep learning mechanism has been described for efficient object detection. The image insight detection is performed through deep learning via auto-stack encoding process. The accuracy and precision of proposed application is getting improved since YoLo v3 work along with RCNN.

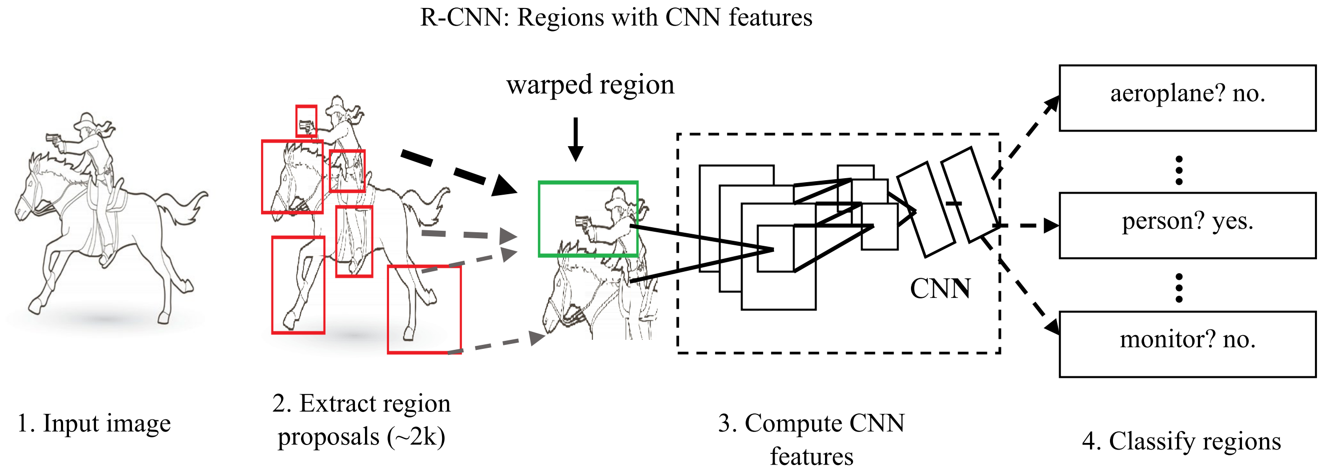

Fig. 3 - Proposed RCNN-YoLo V3

The above figure 3 briefly explains about YoLo V3 based RCNN mechanism, in this stage, pre-processing has been applied on DaSCI dataset. The dataset is getting normalized through RCNN auto stack filtration process. In pre-processing applied image is bounded with colored boxes. The common objects and weapons are classified based on RCNN deep learning model. The training dataset distinguishes weapons and general objects using YoLo V3 background as well as handled similarity. From the name itself R-CNN denotes region where object detection task takes place in a particular region. It was started by [5], it was the first work to propose that R-CNN can be used for detection of objects on PASCAL VOC datasets. It consists of four modules along with target analysis. An independent region proposal is generated by the first module, and a fixed-length feature is extracted by the second module. Images are classified and extracted using a third module in the architecture. In order to ensure accuracy, the fourth module creates bounding boxes around the object in the image. According to the suggestion, around 4096 vectors can be extracted. The figure 3 is the procedure of how the detection of an object works. An image is taken as input and extraction of regional proposals are identified. By extracting and computing the CNN features detection has been performed.

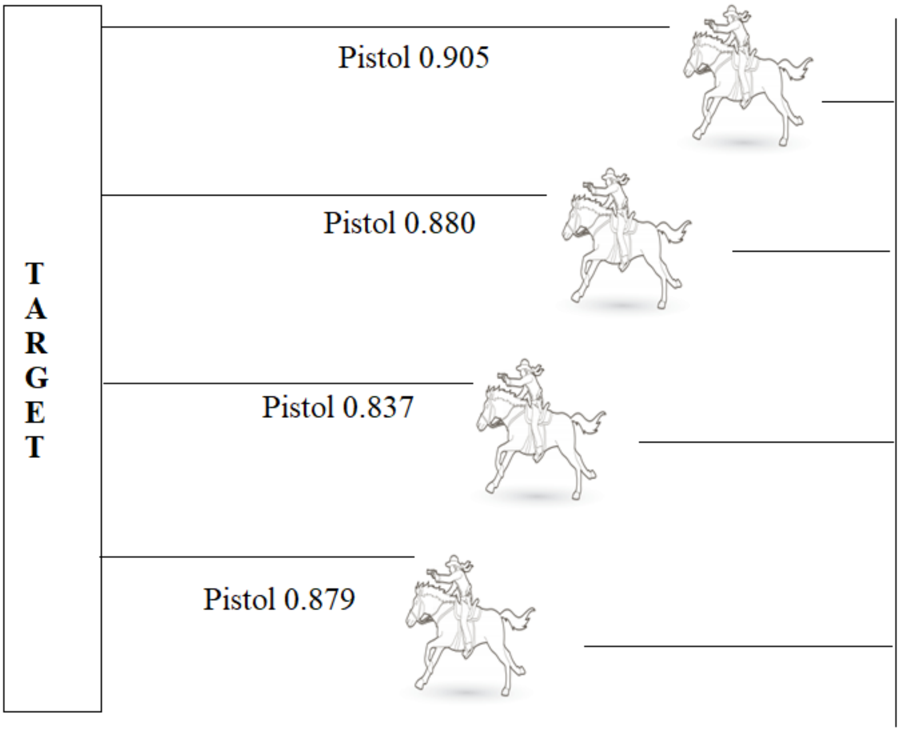

Fig. 4 - Weapon detected with a box and it's labelled with accuracy

Figure 4 describes the output of detected and labeled target whether given or not, if given what's the accuracy of that prediction has been mentioned clearly. The R-CNN executes a Convnet it passes the selection of regions without sharing the computation. The Fast R-CNN, on the other hand, extracts the features from an image once and sends them for classification and localization at once. Another improvement is the use of a ROI pooling layer to extract a fixed-size feature map from an area with varying sizes. The above architecture were the whole input image and region proposals are considered in one forward propagation. It combines all the parts of architecture into single unit such as Convnet, ROI pooling, and classification layer. The (Fast R-CNN + RPN): Another update was added after RCNN to fast R-CNN as it improves the CNN baseline. The only difference when compared to fast R-CNN is it uses RPN (regional proposed network to generate the regional proposals. For an instance R-CNN and Fast R-CNN use CPU based regional proposed algorithms where it takes 2 seconds for computation of an image i.e. it is faster when compared to convolutional network RPN. This reduces the time to 10 milli seconds per image which lead to the overall improvement in the feature representation. Image search architecture is shown in Fig. 3, which produces 2000 proposals per image and is selective. The vast majority of training time has been replaced by the region proposal network. The RPN takes a feature map and generates the anchor and these are passed to classification and regression layer and therefore localizes the bounding box where the object is present.

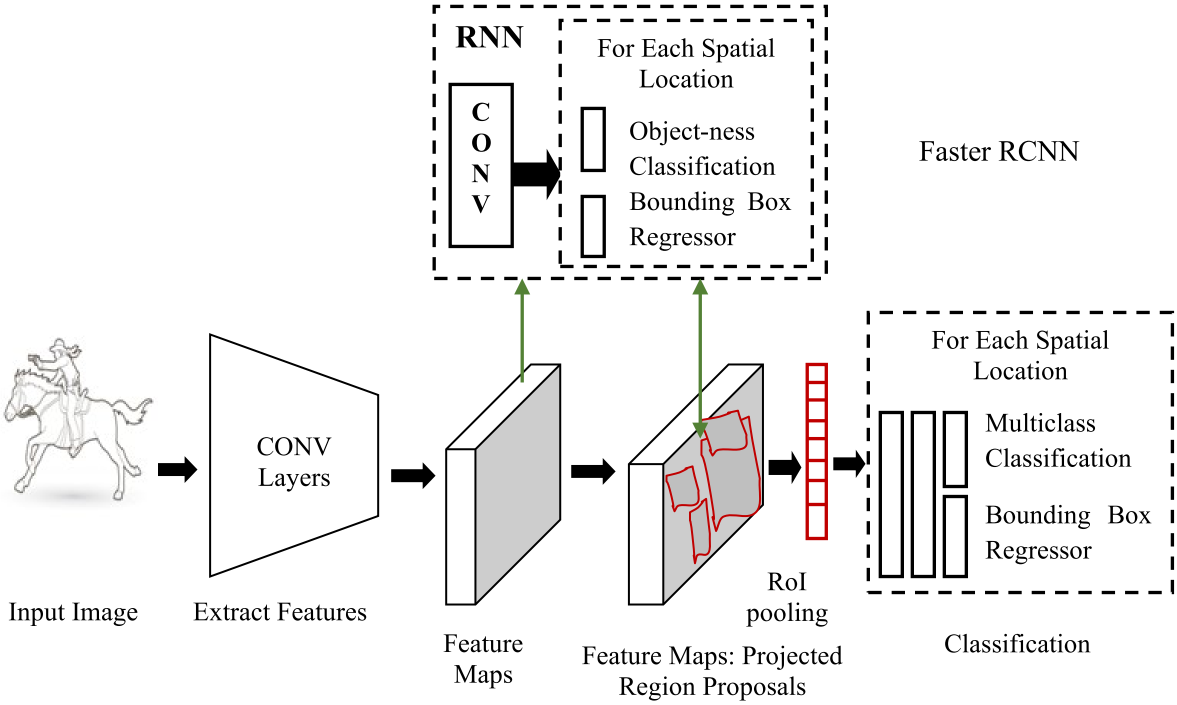

Fig. 5 - Faster R-CNN with RPN architecture

It is the updated version Faster R-CNN with the instance segmentation. Mask R-CNN is compared with accurate object detector as well as estimated samples. Its conceptually very simple but implementation with past techniques are little bit complex. The following functionality is simplified through faster R-CNN. A Faster R-CNN FPN (feature pyramid network) extracts features and delivers high accuracy as well as improving processing speed in the initial stages. As the FPN extracts the relevant and significant features from the lower resolution feature maps, the higher resolution feature maps are essential for recognizing small objects while the lower resolution feature maps are rich in semantic information. Fig 5 is the architecture of Faster R-CNN with instance segmentation framework procedure. Here mask output is different from class output as well as box output is object oriented with respected to uses of Fully Convolution Network's.

3.1 YOLO: You Only Look Once

(YOLO) is the one stage object detector proposed by Redmon, after faster R-CNN the YoLo method can contribute to the real time detection using images and videos. YOLO has been increasing speed of 45 fps without any batch processing on GPU. The pipeline distribution with images can providing detection of harmful objects easily. The result is obtained from multiplying two parts i.e probability of the box P and IOU (Intersection over union) which tells us the accuracy of the object contained in a box. Resulting of YOLO was not at all accurate and localization error was the reason behind the prediction error. The YoLo is Architecture with 24 convolutional layers that act as feature extractor with two fully connected layers. Therefore, YoLo V3 is called in place of V1 and V2 architectures.

3.1.1 YOLO v3

It is considered as the update of first version where they tried to add series of design decisions from the earlier study to improve the accuracy and precision. Some of the additions are:

3.1.2 Batch Normalization

Due to the stochastic gradient descent used for optimization, it is impossible to normalize the full training dataset (SGD). The mean and variance of each activation can be estimated by using the micro batches of activations. Convergence and regularization of the model are made possible by adding a BN layer to YOLO V2 above the convolution layer. Batch normalization boosts the mAP rate by 2%.

3.1.3 High Resolution Classifier

The classifier has the input resolution of 224 x 224 and it raises to 448 at the time of detection. The classification provides us with 448 x 448 resolution with 10 epochs on ImageNet dataset which improves the mAP at 4%.

3.1.4 Convolutional with the Anchor Boxes

The coordinates of the prediction boxes are directly generated by fully connected layer. It adopts this process and removes the fully connected layers. Then prediction takes place which gives the output with 7% increase in mAP therefore YOLO v3 achieves the highest detection rate with precision using the above improvements. The YOLO v3 architecture which contain fully connected layers (highlighted) which replaces predicting bounding boxes with anchor boxes prediction.

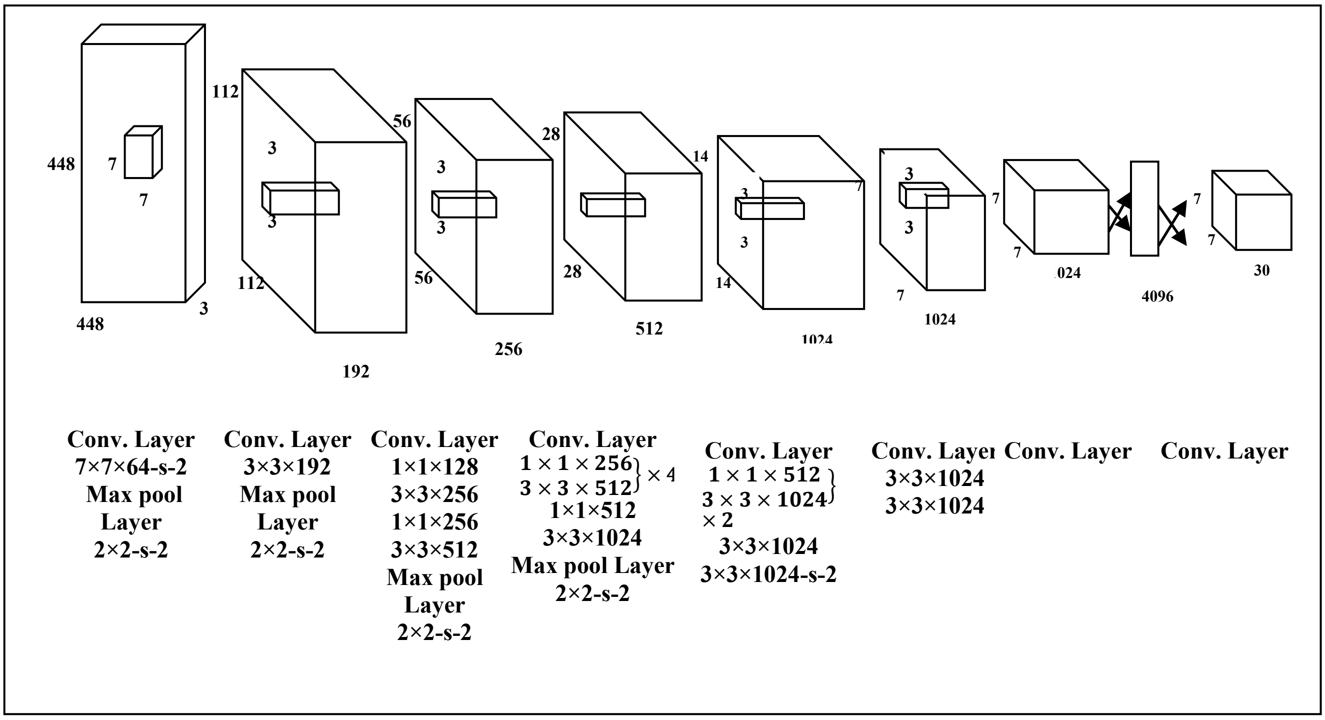

Fig. 6 - YoLo V3 architecture

The above figure 9 shows that YoLo V3 architecture, in this 1024 convolutional layers used for features extraction and 512 and two fully connected layers are working for classifications purpose.

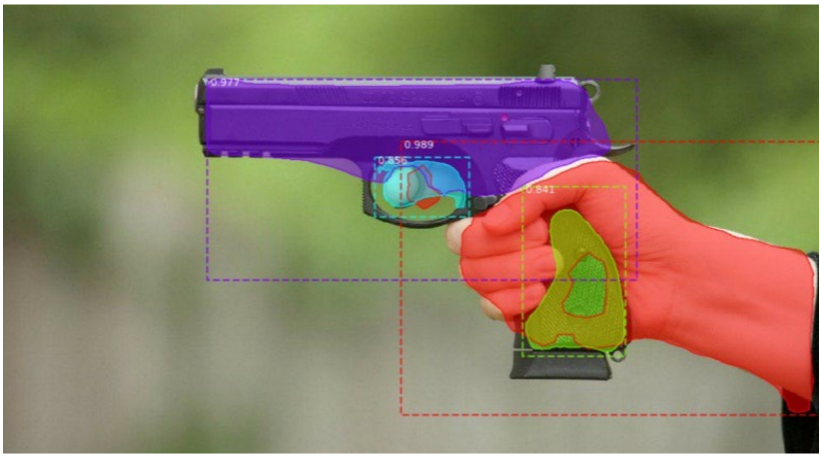

Fig. 7 - Gun detection in the form of mask (image segmentation)

The above figure 6 explains about clear picture of gun detection process with Faster RCNN, in this input image is loaded to as well as classified through faster segmentation. The X, Y, W, H are coordinates which are most helped for bounding box framing. The following concept is called as RoI (region of interest), the superimposed coordinates are get providing infromation about hidden samples according to faster segmentation process.

Algorithm: Faster R-CNN YoLo V3

Step :1 load input image
$Int = load\ (.*\ images);$
Step:2 Apply Faster R-CNN on input image
for a=1: n
loop= a(n);
features =load(temp)
end
step :3 detection using YoLo V3 for classification
Class (YoLo V3) => temp;
Step :4 object detection
Obj(class);
For i : n
I=i++;
Obj(temp) ++1
While
N==n:
Execute from loop
End
Step :5 stop the process

The above algorithm is clearly explaining about Faster R-CNN with YoLo V3 technique, using this technique all hidden samples are detected with bounding box modeling. The for loop on feature extraction and while loop on object classifications have been playing important key role. Finally, this technology is accurately identifying the deep hidden samples on input image.

3.2 Dataset & Metrics

3.2.1 PASCAL VOC DATASET

The research was carried out from 2005 to 2012 for the detection of basic categories of objects, which lead to the creation of series of datasets. This consists of 20 object categories with huge count of images (11000 approximately). categories where further divided into 4 types vehicle, animals, household objects and people.

3.2.2. MS COCO

It was developed by Microsoft and named as Microsoft Common object in Context (MS COCO) for detecting the objects which are there in our surroundings. This consists of 91 object categories with 81 categories have 5000 labelled instances. The total dataset has 2,500,000 labelled instances with 328,000 images. MS COCO considers from all perspective of objects present in the natural environment. This is the best dataset till date.

4. Weapon Detection Procedure

Programming is done in Google COLAB cloud which has free GPU by NVIDIA. It can also be used to develop deep learning applications using libraries like KERAS, TENSORFLOW OpenCV. As COLAB works on google drive one should specify the necessary folder required then import everything present from that folder to the drive.

4.1 Data Collection & Description

The dataset consists of various weapons which are guns, knife etc which was collected from https://www.kaggle.com/datasets . Kaggle platform helps the users to get datasets and build web base models. The dataset consists of images which is not enough to detect the weapon so need label it using LABELLMG.

4.2 Data Processing

Processing of data by drawing a box and label it using LABELLMG software and save the process. will do same with all the images. At the end we will find the dataset consists of images and txt files which has the coordinates of object in an image. The dataset folder is imported in our google drive.

4.3 Darknet

It is the open-source framework for training neural networks written in CUDA and acts as base for YOLO.

Clone Darknet:
git clone https://github.com/pjreddie/darknet.git

- Compile Darknet using Nvidia GPU
- Configure Darknet network for training YOLO v3.
- Extract Images.

4.4 Split Training / Validation Dataset

As there is a possibility of over fitting the data is split into two different parts.

- Training Set
- Validation Set

It is based on the images present in the dataset and can split them in our desired ratio of validation and training. Once the training is done weights will be saved in our google drive which will be used to predict the object in an image. As the obtained training weight use OpenCV to load YOLO v3 architecture and use it for prediction. Above process shows the initial step for training the dataset. After training weights are obtained which can be used for detection.

4.5 Learning Rate

The current weight value is determined by a parameter called the learning rate. To describe the gradual decline in learning rates over time (training epochs), term "learning rate decay" is used.

Table 2 - Maximum accuracy prediction (mAP) of different models

Model	Maximum Accuracy Prediction(mAP)	Frames per second (FPS)	Real Time detection
CNN	61.5 %	5	Not possible
R-CNN	62.2 %	7	possible
Faster R-CNN	68.1 %	18	possible

The above table 2 explains about maximum accuracy prediction (mAP) of different models whether is supports real time system and frames per second. In this analysis, proposed Faster R-CNN model attains more improvement in terms of FPS and real time detection.

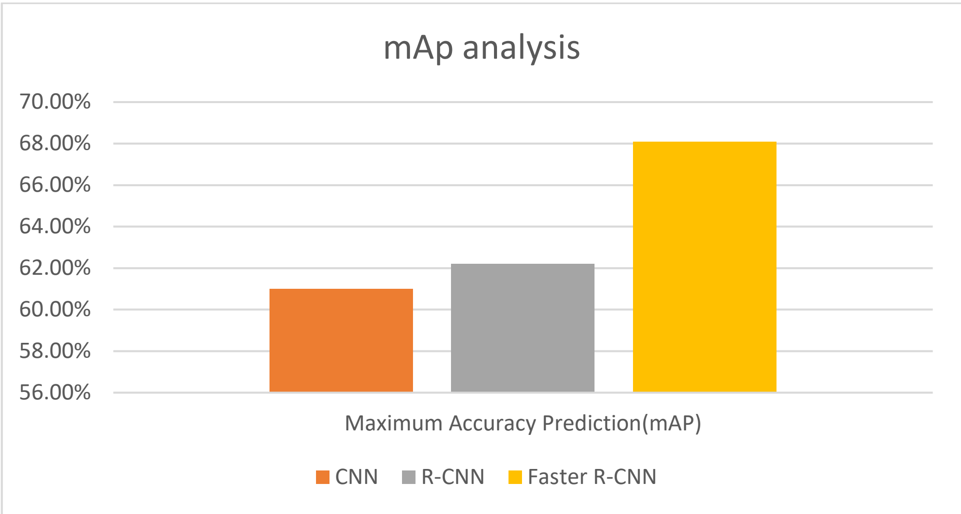

Fig. 8 - mAp analysis

Figure 7 is the bar plot of various models and mAP analysis, in this graphical analysis proposed faster R-CNN attains more improvement in terms of mAp analysis. The CNN 61.5%, R-CNN 62.2% and faster R-CNN 61.8% has been attained.

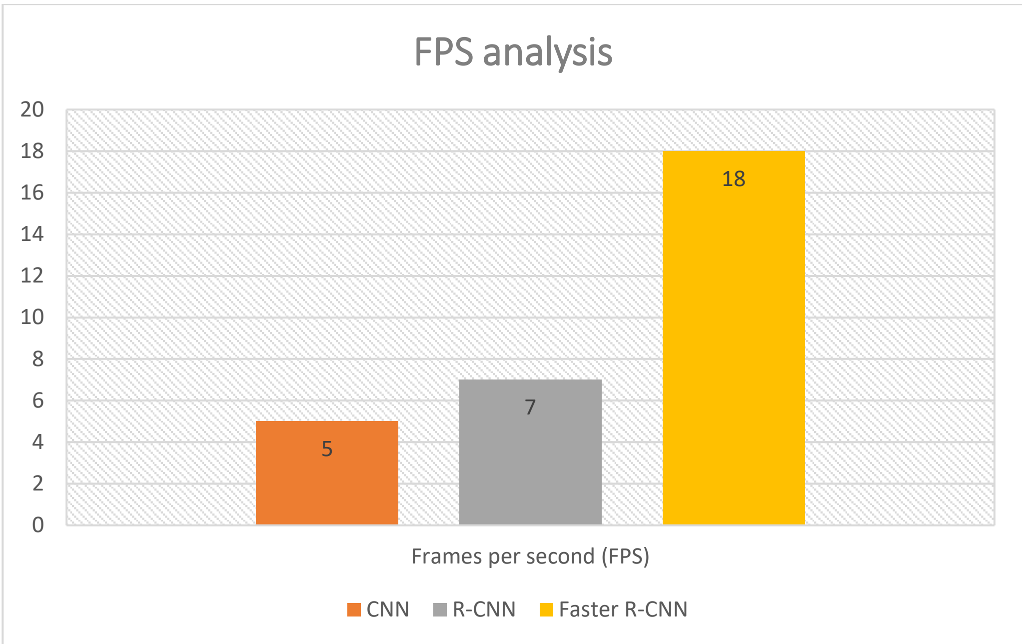

Fig. 9 - FPS analysis

The above figure 8 clearly explains about FPS analysis. The FPS CNN 5, R-CNN 7 and faster R-CNN 18 have been attained. The real time detection is cannot possible through CNN mechanism. The RCNN and faster R-CNN methodologies were extracting real time detection but the accuracy of detection rate has been reduced. Therefore, YoLo mechanism and it's dependency is necessary.

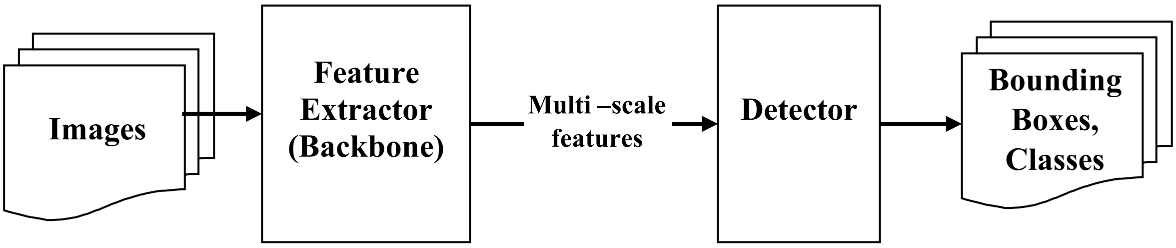

Fig. 10 - YoLo flow diagram

The above figure 10 shows YoLo v1 v2 v3 versions way of predicting the object by making a grid on a particular image which makes easy to identify the object.

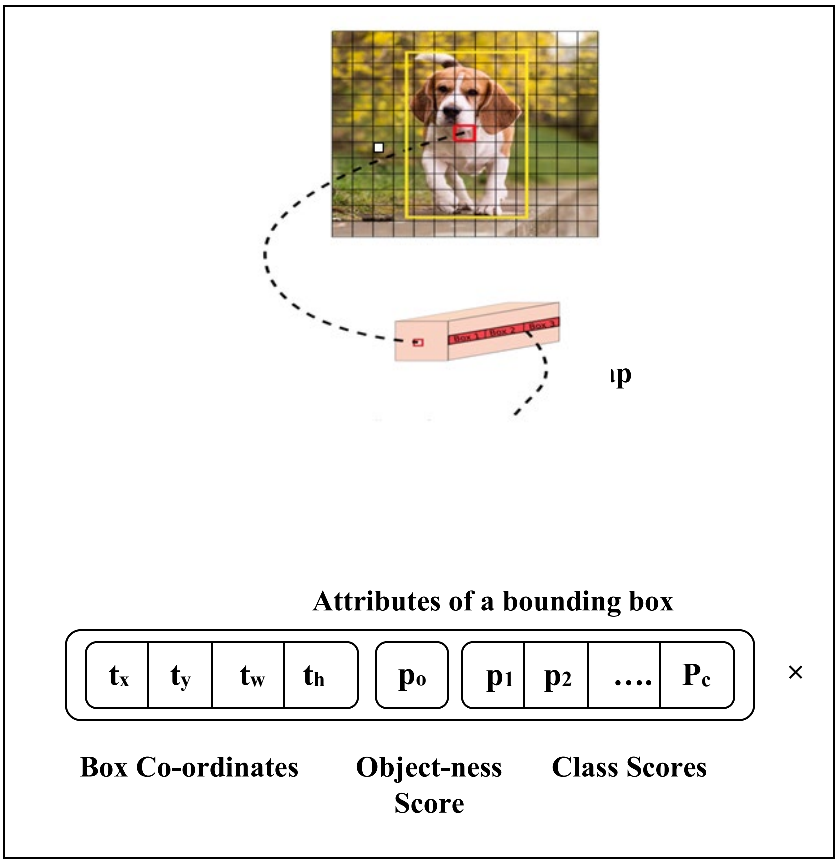

Fig. 11 - YoLo output format

The above figure 11 explains about clear picture of YoLo format, in this technique, coordinates are detecting object scores and class scores. The above analysis has been supported through bounding box concept as well as internal features tracking. The dog neck has some hidden infromation, that samples are clearly identified through Faster R-CNN with YoLo technology.

Table 3 - Comparison of YoLo

Model	Maximum Accuracy Prediction (mAP)	Frames per second (FPS)	Real Time detection
YOLO	63.4	45	Possible
YOLO v2	78.6	40	Possible
YOLO v3	82.9	50	Possible

The above table 3 include various model information and respective accuracy and real time values, in this analysis YoLo V3 is attained high accuracy 82.9 and FPS is 50 i.e more improvement compared to v and v2.

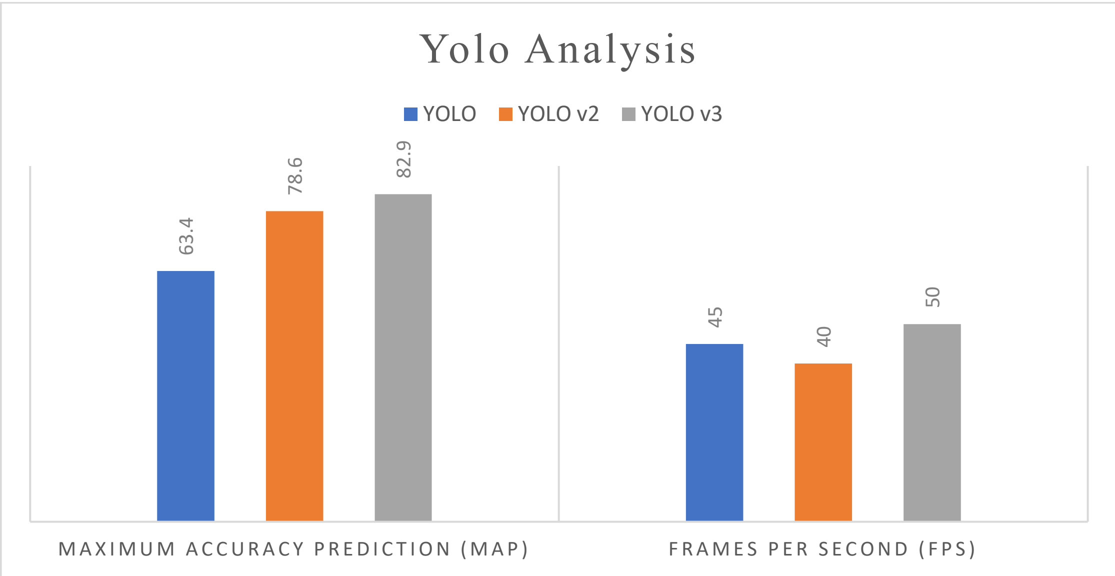

Fig. 12 - Below bar graph shows the mAP comparison of YOLO

The above figure 9 is clearly explains about performance analysis of maximum accuracy analysis as well as frame per second. In this mechanism YoLo v3 attains more improvement compared to V and V2.

5. Results

When the Program is run in OpenCV it will display output which detects the different weapons in a particular image. All the above outputs are for images and for real time detection use our webcam to detect the weapon.

Fig. 13 - Output 1 gun

Fig. 14 - Output 2 knife

Procedure is same but change the coding part in open cv as use our webcam to detect the object which is weapon. From fig 13 man is catching a gun is highlighted in a box with a label represent the detection of weapon, fig 14 show the man catching a knife which is highlighted and marked with a label, fig 15 is the real time detection using webcam is done by holding a knife in hand will in return display the output as shown

Fig. 15 - Real time object detection using webcam

The above analysis is clearly giving information about object detection with Real time camera, in this study knife and pistol have been identified through bounding box by Faster R-CNN with YoLo V3 mechanism.

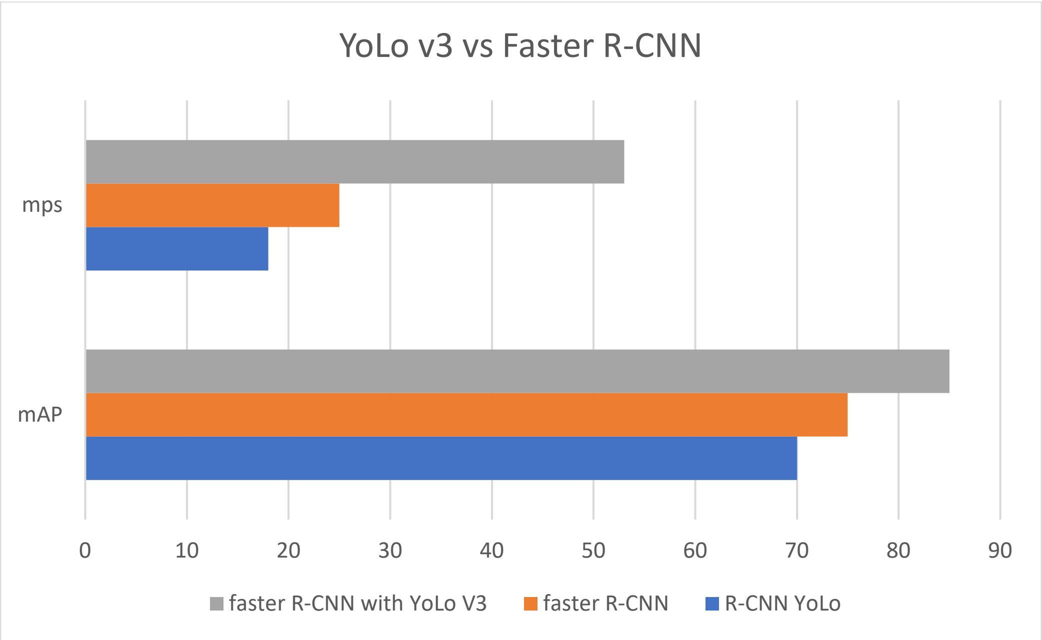

Fig. 16 - YOLO vs R-CNN

The above graph 16 show the comparison of YOLO vs R-CNN side by side, its help us to know which model is faster when compared to past models.

6. Conclusion

In this study harmful object detection has been performed thorough YoLo V3 fused with faster R-CNN. As there are drastic developments being made day-by-day using powerful and advanced equipment, object detection has come a long way with many realistic updates. The attempt for more accuracy and high precision in real time systems considered to be more important. As ultimate goal is to achieve the high accuracy and efficient detectors, researchers came up with many ideas such as modifying the old architecture and implementing changes in the extraction of rich features, improving the processing speed combining both stage detectors to get the better results, increasing the localization accuracy. As the achievement in this domain has been effective but further modification may lead to many big things in real time applications. The study of object detection in images & videos using R-CNN models has bit more prominence compared to YOLOv3 but R-CNN doesn't support real time detection. YoLo plays a key role in real time detection with good average precision results. Therefore, both the models have been fused such that getting high end outcomes in terms of mAP 85%, FPS 53, SSIM 0.99, sensitivity 97.23%, and throughput 94.23% had been attained which are outperformance proposed design.

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