

Identification of Traffic Police Requirements Based On Traffic Concentration Along With Traffic Police Detection

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ABSTRACT

Traffic Detection System plays a vital function in the smart city platform in the current environment. The automated traffic management system's fundamental component is automatic moving vehicle detection from video sequences. In a millisecond, humans can detect and recognize things in complex surroundings. However, in order to transfer that mental process to a machine, we must first master the skill of object detection using computer vision techniques. This article addresses traffic concerns by determining the need for traffic cops depending on traffic density. YOLO v5 and computer vision are used to detect traffic cops. The findings of the investigation suggest that the proposed system can give useful data for traffic surveillance.

I. INTRODUCTION

A major problem is seen in everyday life as people are always in a hurry to reach their offices, schools etc. The population, as well as the number of vehicles on the road, is increasing day by day. Imagine being late to the office one fine morning only to reach a junction where the signal has malfunctioned. All the vehicles you see are congested in the middle of the road with no way for any vehicle to get out. That's when we realise the importance of traffic police. But unfortunately many times they aren't present there.

Hence we came up with a solution of developing a software to avoid major traffic jams and vehicle congestions at rush hours using image recognition and deep learning algorithms.

This software aims to provide solutions to everyday traffic problems by a simple way of alerting traffic policemen of increasing vehicles at a particular signal in a given span of time. Busy roads of India with reckless drivers and untimely signal malfunctions create havoc due to which accidents and delays are prone to happen. Our software will immediately notify the traffic in charge of that particular area regarding the signal malfunction or increase in vehicle activity by installing a basic camera and major road junctions. This will help run traffic police activities smoothly and make people follow traffic laws obediently.

Related Works:

Over 80 literature survey papers were reviewed and researched. It was found out that most of them used YOLOv5 and deep learning algorithms to detect vehicles using a dataset of images. All papers were published after or in 2020.

A model is trained in [1] which uses a large number of preprocessing techniques that gives a higher accuracy rate. Post-processing is also used to eliminate the noise regions and produce a more smooth shape boundary.

The system in [2] is a simple real-time video analyzer. It has the potential to check whether people wear masks or not and thus helps to defeat the widespread COVID-19 virus.

Models trained in [3] have a higher accuracy rate in detecting the speed and vehicles as well. It outperforms other state-of-the-art detection methods. This model is compact and takes up less storage space.

A multi-sensor multi-level enhanced convolutional network architecture is proposed in [4]. Combining this technique with LiDAR captured images not only ensures reliable and accurate vehicle detection but also detects vehicles in different lighting conditions.

[5] presents an advanced DL framework for motorway traffic flow prediction, by chaining together data profiling and outlier identification, spatial and temporal feature generation, and various DL model development.

The model proposed in [6] was able to detect not only terrestrial-captured vehicle images but also images captured from a UAV that has poor quality.

A model which helps in detecting modules of a satellite using video clips as a dataset was proposed in [7].

The strongest advantage of YOLO as compared to similar methods is the speed of 45 frames per second proposed in [8]. Other similar algorithms such as R-CNN and DPM have a much lower FPS.

II. DATASET AND FEATURES

The dataset comprises 200 images that were collected through net scraping from various resources. Various data augmentation and preprocessing techniques were used on the dataset. Data augmentation is a set of techniques for producing additional data points from current data in order to artificially increase the amount of data available. The examination and editing of digitised images, particularly in order to increase their quality, is known as image pre-processing.

The image preprocessing techniques used in this paper are:

1. Auto-orientation
2. Resize-416x416

The following are the data augmentation approaches employed in this paper:

1. Shear: +25 degrees Horizontal, +25 Degrees vertical
2. Horizontal Flip
3. Grayscale
4. Brightness: Between -25% to +25%
5. Blur: Up to 2px
6. Noise: Up to 3% of pixels

By using this our dataset was expanded to 600 images. The dataset consists of policeman images clicked from different angles for the better training of the model. The dataset images were reannotated using the LabelImg tool.

III. METHODOLOGY AND ALGORITHMS

The following methods can be used to process images:

1. Image segmentation
2. Detection of objects.

Object detection is the technique utilised in this paper. Object detection is a computer vision approach for detecting entities in images or videos. Object detection algorithms often use machine learning or deep learning to generate meaningful results. We can recognize and identify objects of interest in photos or video in a matter of seconds when we look at them. Object detection's purpose is to use a computer to imitate this intelligence.

Image segmentation is a technique for breaking down a digital image into subgroups called image segments. This reduces the image's complexity, making it easier to handle or analyse. Segmentation means assigning labels to pixels.

In this paper, we have used two object detection algorithms namely

- I. YOLOv5
- II. Detectron2

I. YOLOv5

The object detection algorithm YOLO ("You Only Look Once"), divides images into a grid system. Each grid cell is in charge of detecting items within itself. Because of its speed and accuracy, YOLO is one of the most well-known object detection algorithms.

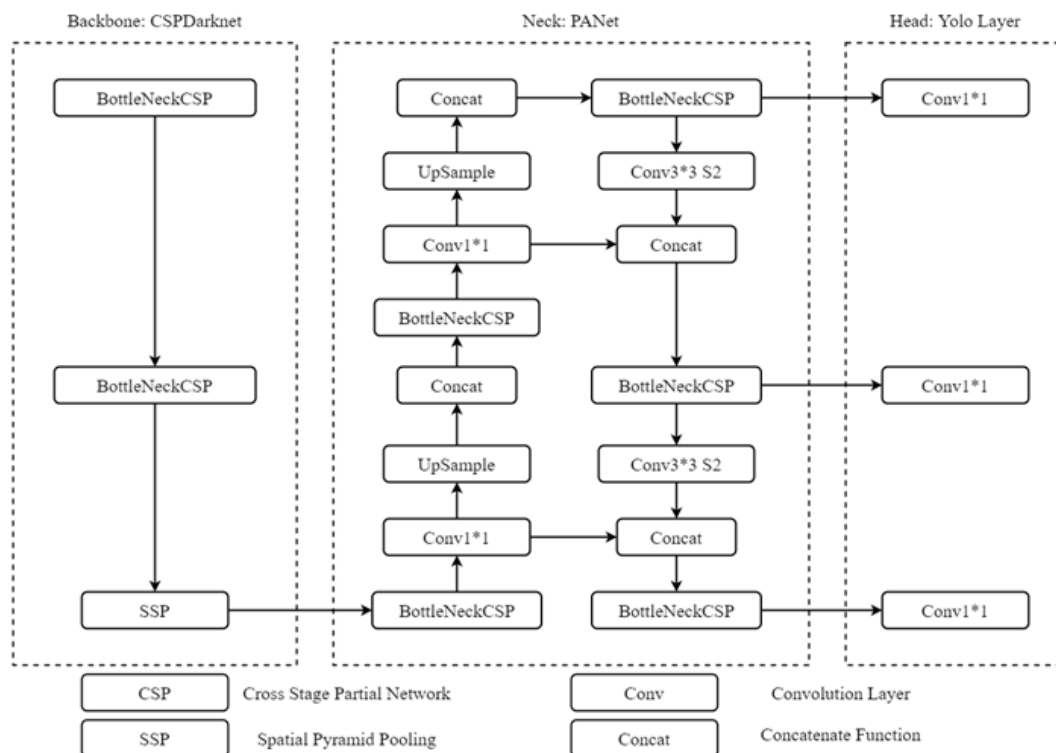


Fig 1.1 YOLOv5 Architecture

Glenn Jocher introduced YOLOv5 utilising the PyTorch framework shortly after the release of YOLOv4.

On GitHub, you can find the open-source code. The IoU score indicates how near the predicted box is to the actual box. It has a range of 0.0 to 1.0, with 1.0 being the best result. The box is characterised as Positive since it surrounds an object when the IoU is larger than the threshold.

'mAP' is a prominent assessment metric in computer vision (i.e. localization and classification). Localization establishes where an instance is (e.g., bounding box coordinates), while categorization describes what it is (e.g. a dog or cat).

The mean Average Precision, or mAP score, is calculated by averaging the AP over all classes and/or the total IoU thresholds, depending on the detection challenges available.

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Yolov5's network architecture is divided into three sections:

- (1) CSPDarknet is the backbone,
- (2) PANet is the neck,
- (3) YoloLayer is the head.

The data is first supplied into CSPDarknet, which extracts features, and then into PANet, which fuses them. Finally, Yolo Layer gives you the results of your detection (class, score, location, size).

Yolov5's Benefits and Drawbacks:

It's about a third of the size of YOLOv4 (27 vs 244 MegaBytes). It's around 180 percent faster than YOLOv4. On the identical assignment, it's about as accurate as YOLOv4 (with a slight difference of 0.003 mAP). The fundamental issue is that, unlike prior YOLO versions, there is no official paper for YOLOv5.

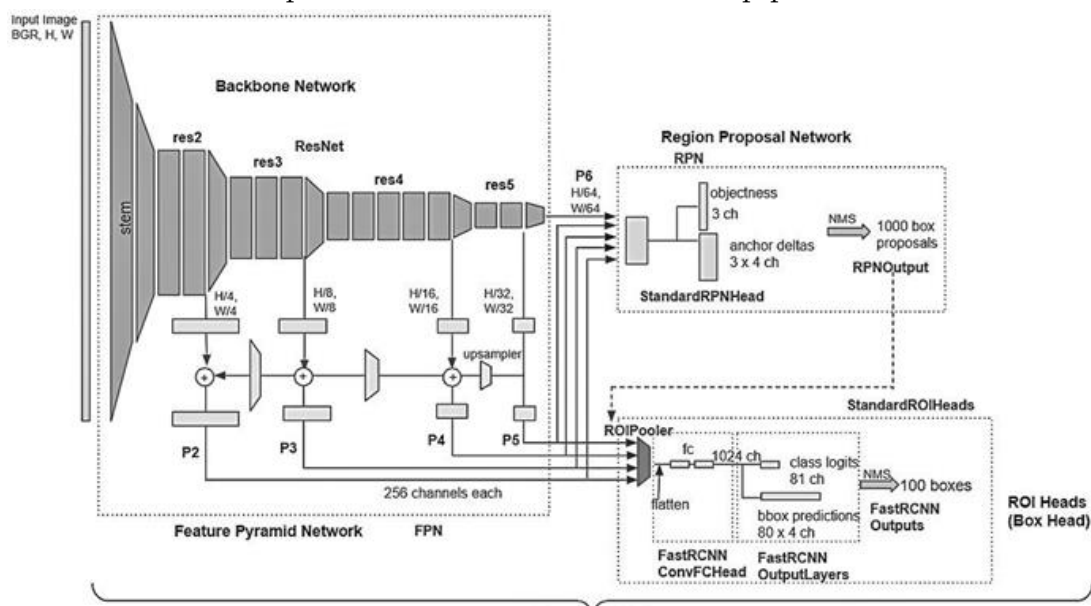


Fig 1.2 Detectron2 Architecture

II. Detectron2

Detectron2 is a complete rebuild of Detectron, which was first released in 2018. Caffe2, a deep learning framework funded by Facebook, was used to create the precursor. Caffe2 and Detectron are no longer supported. Caffe2 is now included in PyTorch, and its successor, Detectron2, is built entirely in PyTorch.

Detectron2 aims to promote machine learning by providing quick training and tackling the challenges that businesses experience when transitioning from research to production. If we need to quickly train an object detection model with a specific dataset, Detectron2 comes to the rescue. The COCO dataset is used to train all of the models in Detectron2. On the pre-trained model, we only need to fine-tune our custom dataset. The Detectron2 has a variety of Object Detection models to choose from. Instance Detection is one of these.

The classification and localization of an object with a bounding box around it are referred to as instance detection. The Faster RCNN model from Detectron2's model zoo will be used to determine the language of text from photos in this article. Object detection can be conducted on any custom dataset using Detectron2.

IV. RESULTS

To evaluate custom YOLOv5 detector performance, we have taken the help of TensorBoard's Scalar Dashboard. The model has been trained on 400 epochs for the YOLOv5 method.

The metric mAP (mean Average Precision) is widely used to evaluate the accuracy of object detectors such as the Faster R-CNN, SSD, and many others. Precision is a measure that assesses the accuracy of your predictions. In other words, the percentage of your predictions that are correct is high. Recall assesses your ability to find all of the positives. The algorithm's ability to detect an object's centre and how effectively the projected bounding box encompasses an object that is measured in box loss.

The probability of finding an object in a proposed zone of interest is measured by objectness. The image window is likely to contain an object if the objectivity is high. The classification loss indicates how well the algorithm can predict an object's exact class.

The model's precision and mean average precision improved significantly before levelling out after roughly 100 epochs. The highest possible mAP score was 0.791.

Around 50 epochs, box loss starts to decline abruptly. Losses in classification stay constant.

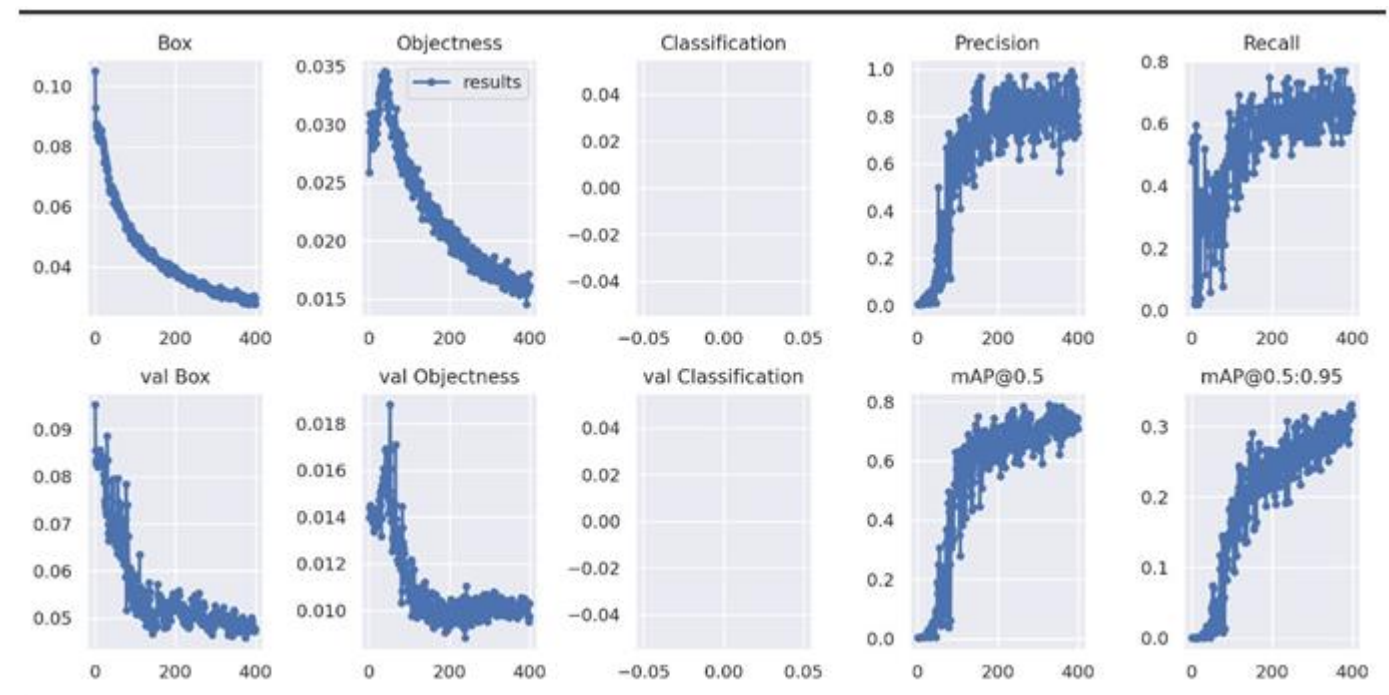




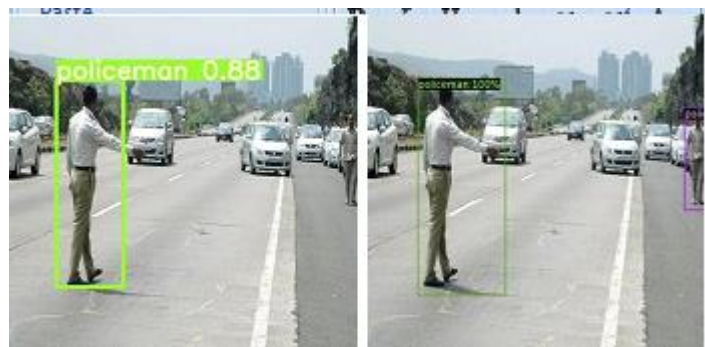
Fig 2.1 YOLOv5 Results

After 50 epochs, object losses likewise exhibit a significant reduction.

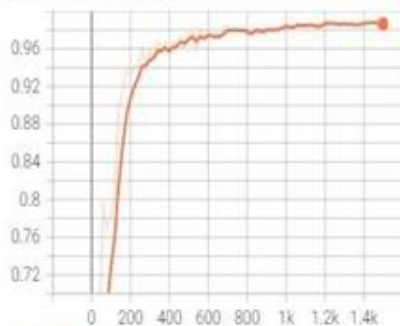
Detectron2:

When determining mAP, the Intersection over Union (IoU) score is used. It's a value between 0 and 1 which indicates how much the expected and ground truth bounding boxes overlap. An IoU score of 0 indicates that the boxes do not overlap. An IoU score of 1 indicates that the boxes' union is equal to their overlap, indicating that they are perfectly overlapping. This model was trained on 1500 epochs with the Detectron2 algorithm. This model has a precision score of 0.505 and a recall score of 0.491 on the IoU scale.

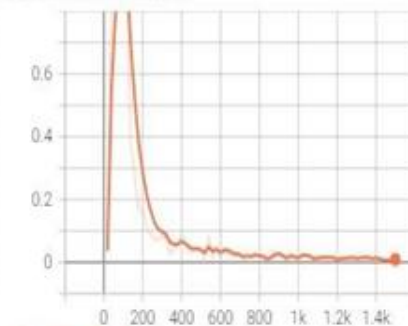
Also, we noticed that in the two models that we have trained, the Detectron2 is not able to distinguish between a pedestrian wearing white clothes and a traffic policeman. In some cases, there were false positives detected by Detectron2. But in the case of the YOLOv5 algorithm, it was able to distinguish between the pedestrian and the policeman. Differences as follows:



fast_rcnn/cls_accuracy
tag: fast_rcnn/cls_accuracy



fast_rcnn/false_negative
tag: fast_rcnn/false_negative



fast_rcnn/fg_cls_accuracy
tag: fast_rcnn/fg_cls_accuracy

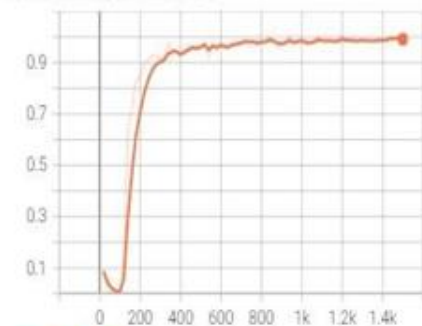




Fig 2.2 Detectron2 Results

V. CONCLUSION AND FUTUREWORK

In this paper we introduced Object Detection for Indian Traffic Policeman Detection. The YoloV5 and Detectron2 Algorithms are used in this study. The model was detecting a policeman from features like his White shirt and Khaki colour pants. The model was successfully able to distinguish a police officer and a normal pedestrian wearing a white shirt. As Policeman Detection hasn't been implemented yet, we cannot compare these results with any other research papers. Based on the work presented in the study, The IoU score for the Detectron2 algorithm is 0.505 and the mAP score for the YOLOv5 algorithm is 0.791. The lack of dataset was a limitation; however, by expanding the dataset, the study could be improved. In the future, if new algorithms are discovered to yield better results, they can be used to improve Policeman detection.

A future upgrade to the project will be a smart signal. The signal will allow vehicles to pass on the basis of traffic in the current path. For example, if a junction of four roads is present in a heavily populated area, the signals on the junction will use our algorithms to detect the number of vehicles passing through each of the four roads. The road having the highest number of vehicles will be given the first priority and will be allowed to pass with an opening of 30 seconds. The road with fewer vehicles than the first will be given less priority and hence will be open for a less period of time depending on the number of vehicles. In this way, the wait time, as well as the traffic flow, will be coordinated with ease.

From the given two images we can infer that Detectron2 is not able to distinguish a normal pedestrian wearing a white shirt from a traffic policeman, which is not the case for the YOLOv5 model. Also, in the case of the Detectron2 model, there were more false positives compared to the YOLOv5 model. The time taken for the YOLOv5 model was much less compared to the Detectron2 model. Based on the work presented in the study, it is plausible to conclude that the YOLOv5 model outperforms the Detectron2 model in aspects of computation time and accuracy.

VI. REFERENCES

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