Improve Detection and Tracking of Pedestrian Subclasses by Pre-Trained Models

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(Received: 6-Feb-2022; accepted: 5-Jun-2022; published: 30-Sep-2022)
DOI: http://dx.doi.org/10.55579/jaec.202263.369

Abstract. *There are sub-classes of pedestrians that can be defined and it is important to distinguish between them for the detection in autonomous vehicle applications, such as elderly, and children, to reduce the risk of collision. It is necessary to talk about effective pedestrian tracking besides detection so that object remains accurately monitored, here the effective pre-trained algorithms come to achieve this goal in real-time. In this paper, we make a comparison between the detection and tracking algorithms, we applied the transfer learning technique to train the detection model on new sub-classes, after making Images augmentation in previous work [1], we got better results in detection, reached 0.81 mAP in real-time by using Yolov5 model, with a good tracking performance by the tracking algorithm dependent on detection Deep-SORT.*

Keywords

Deep Learning, Yolov5, Deep-SORT, Pedestrian, Detection, Tracking.

1. Introduction

Road accidents are still responsible for 1.3 million deaths each year, and worldwide there are nearly 50 million injuries, in the United States, child trauma cases have reached more than 1.5 million cases, and this has led to 600,000 admissions to the hospital and between 15 to 20 thousand deaths among children annually. Also in China, it was continuously found that collision accidents are among the first three causes of death among children during the period between 2004-2011 [2].

Besides, a study on the external causes of accidents carried out by the SEADE Foundation in Brazil found that road accidents and falls are one of the main causes of death among the elderly, and the external causes have less impact after comparing other causes of death among those populations [3].

Based on the foregoing, improving computer vision is one of the most important solutions in driver assistance systems and self-driving cars, to achieve better detection and tracking of pedestrians, in particular (children and the elderly). Where deep learning methodologies have proven excellent effectiveness in this field, here our work comes on pre-trained models and techniques for dealing with them in the transfer of knowledge in the detected and tracked objects like Pedestrians. Pre-trained models are trained on a very wide range of image classification problems [4]. Convolutional layers act as feature extractors while fully connected layers act as classifiers as shown in Fig. 1.

A conventional neural folding network consists of conventional Layers and aggregation layers culminating in a fully connected layer followed by a two-output classification layer [5].

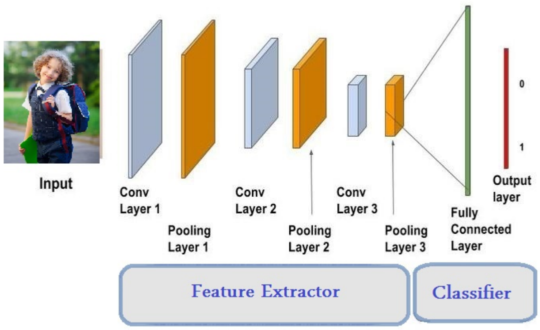

Fig. 1: Simple Convolutional Neural Network (CNN) architecture [5].

These models tend to learn very good separator features because they have been trained on a large number of images. We can use the convolutional layers as a feature extractor and this approach is known as transfer learning [4].

2. Transfer learning

As a general rule, when we have a little training data set and the issue to be illuminated is comparable to the task on which the pre-trained models were initially trained, at that case we will utilize a Transfer learning approach. Whereas in the case of we have sufficient data, at that point we are able to try to alter the convolutional layers in neural network to learning more capable powerful features about the problem to be solved.

So the goal of transfer learning is to improve the performance of the model, by transferring existing knowledge in multiple areas but related, where we can reduce reliance on large amounts of training data.

In a survey study by (FUZHEN et al.) [6], on more than 40 representative approaches to transfer learning, the study showed the importance of choosing Learning models suitable for practical application.

The study also indicated the need for new approaches to solving transportation problems within more complex scenarios, such as what is happening in the real world. This underlines the importance of relying on this approach to improve our "you only live once" YOLO model for the detection of other pedestrian subclasses.

Likewise, Ayachi and Afif [7], proposed a pedestrian detection system based on CNN, a deep learning model, called the proposed model tiny YOLOv3 and the Performance of Mean Average Precision (mAP) was 76.70% and an inference time is 202 "Frames per Second" Fps, then after applying transfer learning to the new images, the efficiency reached 98%.This confirms the effectiveness of the Yolo model, on which we seek to apply the transfer learning technique, in our new dataset of images.

Also in a study, Hu et al. [8],in agreement with the previous study but was for infrared pedestrian detection and based on a comparison of the Yolo v3 model and Faster R-CNN, and the application of transfer learning, it showed that the average detection precision using the ImageNet model that was previously tested is 83.34%, while with the new model, it reached 84.78%, this confirmed again that the method of transfer learning is effective in the field of deep learning, especially with infrared detection applications.

In the study of Zhang et al. [9], whose work was to perform an Unmanned Aerial Vehicle (UAV) detection model for an active laser imaging system, transfer learning was used in a deep learning model on a simulation dataset to identify aircraft features, and testing is done on a real environment, the experimental results were that the performance has been improved where the Precision in the Yolov5s model was up to 1.00 and the speed was up to 104.167 FPS. We conclude, despite the high accuracy here, that there is a possibility of overfitting, but this does not cancel the effectiveness of the Tolov5s model for real-time detection performance.

In an important study by Wen et al. 2021 [10], they confirmed that YOLOv5 is an excellent objects detection algorithm. Over the years of development, the algorithm architecture has been constantly improved to maintain the advantage of faster detection speed while maintaining high accuracy. The YOLOv5 algorithm has a great opportunity in future detection work; this method has great applicability in real life. In terms of the tracking Jie et al. [11], whose paper was about Naval Ship Detection and Tracking, he proposed the developed Yolov3 as detection algorithm and the DeepSort as real-time deep tracking algorithm, through improvements they made to Yolo using the Kmeans clustering algorithm, stated the improved YOLOv3 in DeepSort has extra overall performance in complicated scenarios and is more efficient with camera movement and occlusion compared to modern algorithms such as MOSSE, KCF, TLD, MIL and Media Flow, and the results showed an increase in the average Precision and the frames per second for this improved algorithm by about 5% and 2% respectively.

Likewise, Song et al. [12], improved the version of YOLOv3 and incorporated Deep-Sort into the method of detection and tracking. Deep-Sort accuracy, recall and mAP (mean average precision) respectively was (91%, 90%, and 84.76%). After working on data augmentation to address the problem of the unbalanced sampling distribution (a mechanism we used), the remarkable matter about their improvement of the YOLO algorithm is the removal of the corresponding output to reduce its computational costs and improve real-time. The most important point here is to incorporate Deep-Sort into the detection method to improve the accuracy and robustness of multi-object detection and improve Tracking in videos.

So, in a study similar to that we have (low data and pre-trained model), Transfer learning can be used to achieve better results, and the improved Yolo algorithm meets the requirements of accuracy and speed required. It is also the new version of Yolov5 which will give superb results in the accuracy of detecting and speed required at the actual time. In addition, inserting the Deep-Sort algorithm to improve the tracking process led to clearly improving performance.

3. Detection Models

3.1. YOLOv5

There are two updated and better versions of YOLOv3 that came one after the other. The first one was YOLOv4 created by traditional authors Alexey Bochkovski et al. [13], and the second one was YOLOv5 recently released by Glenn Jocher [14].

This new version has received some controversy, as it is not the traditional author of the YOLO series, but after bypassing this controversy, the v5 model showed a significant increase in performance over the previous versions.

And it is proven that YOLOv5 has numerous focal points in the building. A much-appreciated modify is the use of Python rather than C in past versions.

Integrating with IoT devices just got simpler. Besides that, the PyTorch community is additionally bigger than the Darknet community, and PyTorch is beyond any doubt to get more contributions and has extraordinary improvements potential within the future. The YOLOv5 network consists of 3 major parts:

1) Backbone: In this part, there is a convolutional neural network the features of images are aggregated and formed at different scales.

2) Neck : It consists of a series of layers for mixing and merging the features of the image and then passed to the front to do prediction.

3) Head: Takes the features from last part "nec" and take the steps of box and class prediction.

All object detection architectures have in common: The features of the input image are compressed by the feature extractor (backbone) then transferred to the object detector (including detection neck and detection). Neck works as a feature aggregator, tasked to mix and blend the features created within the Backbone to get ready for the coming step within the Detection Head [14].

YOLOv5 presents in different versions, each one has its own unique features, and these models are:

1) Yolov5s - The tiny model
2) Yolov5m - The medium model
3) Yolov5l – The large model
4) Yolov5x - The extra-large model

The analysis of performance for all these models as per Glenn Jocher is provided below in the Fig. 2.

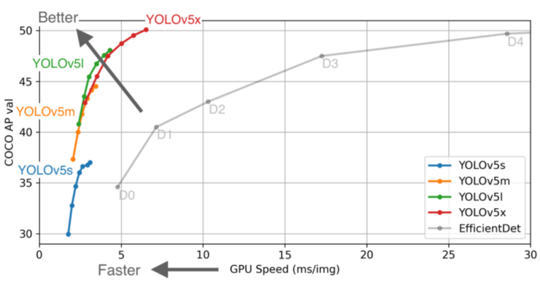

Fig. 2: YOLOv5 stats from UltraLytics repo.

Since our work is focused on detection in real-time, the factor of most importance is the speed, therefore the small model has been chosen as the representative of the family of YOLOv5 for analyzing its performance.

3.2. Single-Shot Detector (SSD)

The SSD algorithm is configured to detect different classes of objects in an image by giving a confidence degree related to the existence of any one of these objects. Basically, the anchor box with the most noteworthy degree of overlap with an object is responsible for predicting that class of object's and its location. This is convenient for real-time applications because it does not revaluate bounding box assumptions (as in Faster RCNN). SSD architecture is based on CNN and to discover target classes of objects, it follows two stages: Extract feature maps, and apply convolutional filters to do objects detection [15].

Tab. 1: Difference between YOLO and SSD.

SI.no.	Parameters	YOLO	SSD
1	Model name	You Only Look Once	Single Shot Multi-Box Detector
2	Speed	Low	Hight
3	Accuracy	80.3% High	72.1% Low
4	Time	0.84∼0.9 sec/frame	0.17∼0.23 sec/frame
5	Frame per second	45	59
6	Mean Avarage precision	0.358	0.251

Table 1 shows a comparison between YOLO and SSD regarding speed, accuracy, time, frames per second (FPS) [16] and mean average precision (mAP), and whether or not they can be used for real-time applications.

3.3. MobileNet-SSD V2.0

It is generally noted that computer vision models are getting deeper and more complex with the goal of achieving greater accuracy. But these advances increase the size and latency so that we cannot use them in computationally complex systems.

In this case, MobileNet will come in handy. this model mainly prepared for embedded applications and mobile that need high speed. In the first version (MobileNetV1) it contains a deep detachable wrapper, which reduces the size of model and complexity cost of network. The 2nd version of MobileNet family , an inverted residual architecture was given for much way better modularity and this version was named MobileNetV2 [17].

Google has released Single Shot Detector (SSD) for applications that rely awfully on accuracy and speed. so the name itself suggests, mainly by a single snapshot, SSD detects multiple objects in an image. Algorithm SSD is intended in a strategy that can be combined with different networks like VGG and MobileNet architecture.

Hence, MobileNet is combined with SSD to outstanding performance and named MobileNet-SSD.

4. YOLOv5 vs MobileNet-SSD

A comparison was made between the two models (Yolov5s & MobileNet-SSD V2) after completing the training process, as shown in Tab. 2. The models were published using two "Nvidia GTX 1660 Ti" and "Nvidia Tesla T4" machines. This was done to define their performance in a high-end and mid-tier CPU. To distinguish between the two models, the factors to consider, two metrics can determine which model will be suitable for your situation. It is the average Precision (mAP) and model processing speed measured over frames per second (FPS) of the output processed video. In the following table, the results of the trained models are shown in the following table.

Tab. 2: Performance analysis of the two models.

Model	mAP (%)	FPS	
		TeslaT4	GTX 1660 Ti
YOLOv5s	37.6	100	28
MobileNet-SSD V2	33.79	94	26

Often while checking the effectiveness of model performance, accuracy is prioritized over speed and for real-time deployment speed is an equally important factor it is important to note, for real-time detection, the accepted fps value is 15.

It can be concluded that YOLOv5s is the best suitable model for real-time situations with optimal values of both accuracy and "FPS" frames per second. It can be argued that MobileNet-SSD V2 offers a speed little similar to that of YOLOv5s, but in the accuracy side it lacks for the real-time purposes.

5. Pedestrians Tracking

In a paper by Jie et al. 2021 [11] on Naval Ship Detection and Tracking, he proposed the developed Yolov3 as detection algorithm and the Deep-Sort as real-time deep tracking algorithm, through improvements they made to Yolo using the Kmeans clustering algorithm, then the output classifier was modified to a SoftMax classifier, and finally, Soft-NMS was introduced to solve problems Shortcomings of the non-maximum suppression algorithm when scanning candidate frames.

The results showed an increase in the average precision and FPS of the improved algorithm by about 5% and 2%, respectively. In terms of tracking, the improved YOLOv3 in Deep-Sort showed that it has more performance in complex scenes and is stronger with occlusion and camera movement compared to modern algorithms such as KCF, MIL, MOSSE, TLD and Media Flow.

In a study of the real-time detection and tracking of small Target Traffic Signs, Song et al. 2021 [12], proposed also an improved version of YOLOv3. After working on data augmentation to address the problem of the unbalanced sampling distribution (a mechanism we used), the remarkable thing about their improvement of the YOLO algorithm is the removal of the corresponding output To reduce its computational costs and improve real-time, the most important point here is to incorporate Deep-Sort into the detection method to improve the accuracy and robustness of multi-object detection and improve tracking in videos, and the work showed improvement in accuracy, recall and mAP respectively (91%, 90%, and 84.76%).

5.1. Tracking algorithms

The detection-based tracking algorithms being worked on here are: SORT and Deep-SORT. These two types particularly are well suited for real-time tracking.

1) SORT

Simple online and real-time tracking, SORT, is a tracking algorithm introduced by Bewley et al. in [18]. SORT is designed to perform Multiple Object Tracking (MOT) in a trace-by-detection system. To achieve real-time processing, SORT uses CNN-based object detectors to rely instead on more accurate object detection.

For each new frame, SORT first publishes the already tracked objects in the current frame. The new positions of these already tracked objects are predicted using a Kalman filter [19] with a linear constant velocity model. Then, the object detection algorithm detects the objects in the current frame. These detected objects are then compared to the already tracked objects and a cost matrix is created. This cost matrix is calculated as the IoU between each discovery and each actually tracked objects. Then, the detection is allocated to the already tracked objects using the Hungarian method. A new path is created when an object is detected in multiple consecutive frames without overlapping any already tracked object. SORT does not contain any memory and the tracked object is lost if SORT fails to detect it in a subsequent frame.

2) Deep-SORT

Designed with the goal of reducing the number of identity switches, Deep-SORT integrates appearance information into the tracing procedure introduced in SORT [20]. Similar to SORT, Deep-SORT handles case estimates using the Kalman filter. Deep-SORT differs from SORT in that it uses additional techniques when assigning discoveries to already tracked objects [21].

Deep-SORT uses two different measures of distance when comparing discoveries to already tracked objects Mahalanobis distance and Cosine distance between appearance descriptors.

The Mahalanobis distance measures how the new detection position differs from the locations of the already tracked objects in terms of standard deviations from the mean of the tracked objects. Using this metric, Deep-SORT can avoid assigning new detection to existing paths that make it unreasonable to move between frames. Appearance descriptors are computed by forwarding each bounding box through a CNN previously pre-trained on a person-re-identification dataset. The appearance descriptor of each new discovery is then compared to the appearance descriptors of already tracked objects by calculating the cosine distance between the descriptors. Tracked objects and their appearance descriptions are also saved for 30 frames after they are lost so that Deep-SORT can resume tracking lost identities for several frames. Using appearance descriptors in this way gives Deep-SORT the ability to find a previously tracked object even if it is hidden for some frames.

6. Methodology for Detection

1) Download Correctly Formatted Custom Dataset (Augmented Data by last study [1]).
2) Loading the pre-trained model (Yolov5s).
3) Defining Model Configuration and Architecture by two ways:
   - Freeze Partial Yolov5s.
   - Freeze fully Yolov5s.
4) Training the Model.
5) Checking the Performance.

6.1. Results

We can see the results of the model after the Full and partial freezing of the YOLO network:

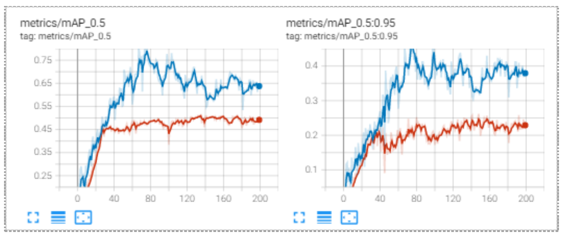

Fig. 3: Metrics "Partial Transfer Learning model blue Color, Full Transfer Learning red Color".

Tab. 3: Results Yolov5s by transfer learning. Model summary: 213 layers, 7,018,216 parameters, 0 gradients, 15.8 GFLOPs.

Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
all	41	73	0.857	0.777	0.813	0.402
Kid	41	32	0.903	0.781	0.822	0.36
Person	41	13	0.75	0.692	0.696	0.346
elderly	41	28	0.919	0.857	0.921	0.499

Since we find here the results of each of Precision, Recall and mean Average Precision (mAP) for our status respectively (0.857, 0.777, 0.813).

$$F1\_SCORE = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Where Precision is intuitively the ability of the classifier not to label as positive a sample that is negative.

Recall is the ability of the classifier to find all the positive samples.

F1-Score is defined as the harmonic mean between precision and recall. It is used as a statistical measure to evaluate performance.

By comparing the value of the F1_Score measure, wherein the previous study was 0.509 after augmenting data [1], we find that measure after calculating reaches 0.815, which means a clear improvement in Recall and Precision metrics. In the following figure (Fig. 4) we see a screenshot of a video on which our detector and tracker have been applied for our sub-classes Pedestrians.

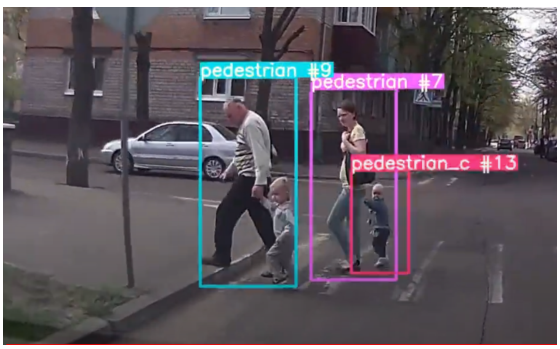

Fig. 4: Detect & tracking for subclasses pedestrians (3 classes).

The Classes are (1- Pedestrian "Person": Normal Pedestrians like man or woman. 2- Pedestrian-c "Kids": Children Pedestrians only. 3- Pedestrian-o "Elderly": Old men and women Pedestrians.)

And in the following figure (Fig. 5) we see a screenshot of a video in which detection and tracking have been applied for all classes.

The Classes like (person ,bird, cat, cow, dog, horse, sheep ,aero plane, bicycle, boat, bus, car, motorbike, train ,bottle, chair, dining table, potted plant, sofa, TV/monitor...etc).

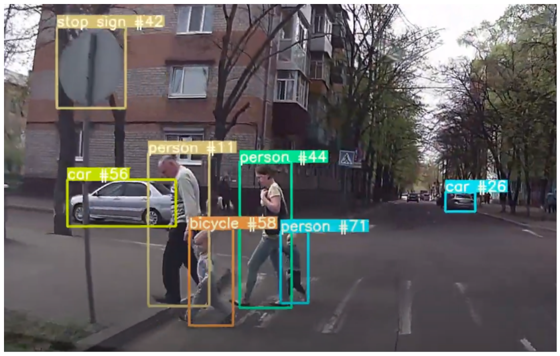

Fig. 5: Detect & tracking for all classes of pre-trained yolov5s (80 classes).

6.2. Discussion

In the process of detecting and tracking pedestrian subclasses, pre-trained detection algorithms are more efficient in training and testing, especially when images of training are limited, and by applying techniques such as partial transfer learning, and then applying detection-based tracking, so the focus is on improving detection primarily.

We concentrated in our work on the issue of comparing detection algorithms and enhancing the dataset for subcategories here, applying transfer learning techniques to the candidate algorithm, and then moving on to tracking these objects.

Our study recommends using YOLOv5s as a detection algorithm and applying partial transfer learning for training, and adopting DeepSORT based on the detection algorithm to do the tracking.

What is new here is the expansion of the detection and tracking of the important sub-classes of pedestrians (the elderly, children), through a limited dataset volume, and we reached good results in this regard with mAP metric reach to 0.81.

One of the strong points of our work is to get good results in detection with not huge amounts of images, and there are limitations regarding adding images due to the difficulty of acquiring images intended for Sub-classes pedestrians in different environments, and the limitations of the computing equipment available for real application.

7. Conclusions

After making a comparison regarding detection, Yolov5s performance was better than MobileNet-SSD V2.0 algorithm (mAP and model processing speed). In a previous paper on studying the effect of data augmentation on the results of the Detection [1], where F1-Score reach 0.509, We improved the detection algorithm by engineering the training technique of neural network by applying partial transfer learning and found that applying the partial transfer learning to the Yolov5s algorithm, outperforms and gives better results in the metrics (mAP, Recall, and Precision) 0.81, 0.75,0.78 in the same order (Tab. 3), and F1-Score reach 0.815. And the partial transfer learning is superior in performance to the freeze of fully connected layers weights (Fig. 3).

Regarding pedestrian tracking, after comparing different algorithms, we found the high efficiency of Deep-SORT which is a detection-based tracking algorithm, the results are good, but its performance basically depends on improving the detection more.

8. Future Work

Improving the detection algorithm by increasing the dataset images, in addition to studying the effect of different types of transfer learning. Besides pedestrians tracking in parallel with improving the detection algorithm, we will study improve tracking performance too, via studying other tracking algorithms non-detection-dependent.

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