Detecting Vehicles on the Edge: Knowledge Distillation to Improve Performance in Heterogeneous Road Traffic

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Abstract

The drastic growth in the number of vehicles in the last few decades has necessitated significantly better traffic management and planning. To manage the traffic efficiently, traffic volume is an essential parameter. Most methods solve the vehicle counting problem under the assumption of state-of-the-art computation power. With the recent growth in cost-effective Internet of Things (IoT) devices and edge computing, several machine learning models are being tailored for such devices. Solving the traffic count problem on these devices will enable us to create a real-time dashboard of network-wide live traffic analytics. This paper proposes a Detect-Track-Count (DTC) framework to count vehicles efficiently on edge devices. The proposed solution aims at improving the performance of tiny vehicle detection models using an ensemble knowledge distillation technique. Experimental results on multiple datasets show that the custom knowledge distillation setup helps generalize a tiny object detector better.

1. Introduction

With the recent advancements in Artificial Intelligence and Computer Vision, object detection techniques are gaining traction, especially in Intelligent Transportation Systems. Object detection for Intelligent Transportation Systems uses traffic cameras or other vision-based sensors. These techniques play a pivotal role in tackling challenging problems such as traffic density estimation, tracking traffic violations, lane changes, detecting speeds of individual vehicles, vehicle classification, and counting. With the recent developments in the field of machine learning for the Internet of Things (IoT), we can receive live analytics and predictions at a low cost using these devices [1, 19].

In this paper, we focus on the task of counting vehicles autonomously in an edge device using computer vision and deep learning. Estimating classified counts using cameras can be seen as the classic object counting task in computer vision [15]. Typically, object counting is the result of object detection and tracking. Therefore, we employ the Detect-Track-Count framework, consisting of three stages: vehicle detection, tracking, and counting. Since the framework is intended to be deployed on edge devices, the models deployed must be compact and computationally efficient. Given that tracking and counting are dependent

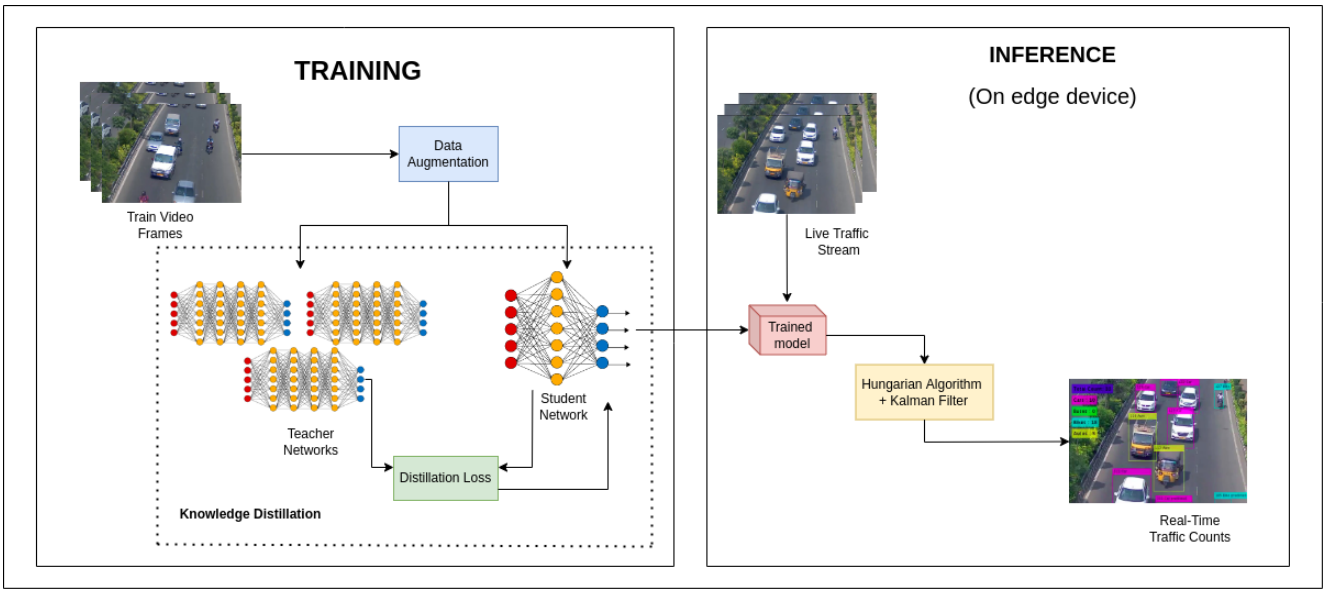


Figure 1. Proposed Architecture

on vehicle detection and have significantly lesser computations, we focus on making vehicle detection robust, fast, and lightweight.

Traditional vehicle detection techniques include Histogram of Oriented Gradients (HOG) [31], Scale Invariant Feature Transform (SIFT) [8], followed by Support Vector Machines(SVM) classification. These models are incredibly lightweight and can easily be fit on edge devices. However, these are not robust to several environmental factors (weather, time of the day), camera angle, and lighting. There emerged a need for a robust model that can handle any scenario in a real-time setup.

These defects migrated the interest of the research community towards deep learning models for object detection, such as Faster RCNN [30] (Region-based Convolutional Neural Networks), YOLO (You Only Look Once) [29], and SSD (Single Shot Detector) [23] for detecting the objects. These models are often very robust and handle dynamic inputs efficiently. However, these models are computationally demanding and need state-of-the-art computing systems to function.

The state-of-the-art vehicle detection for heterogeneous road traffic uses Faster RCNN, trained on Pascal VOC, augmented with a low-resolution dataset [26]. Faster RCNN is a computationally intensive model, and it is significantly slower than the frame rate of incoming video. As a result, deploying the model on an edge device with an average CPU and GPU is not possible. Faster RCNN can be replaced with YOLO to increase performance; however, even YOLO is computationally intensive on edge devices. Switching to even more lightweight models decreases the accuracy substantially.

To make these models lightweight, researchers have tried pruning techniques [25]. However, the increase in speed is not very significant, and if many layers are pruned, the performance degrades even further. Another approach to solving the problem is by using Knowledge Distillation [34]. This is an effective technique, inspired by the human's ability to quickly learn new complex concepts when given very small training sets [4, 14]. In model compression for deep learning, knowledge distillation has been widely used to transfer information from one network to another, i.e., a smaller student model is trained to mimic the performance of a large pre-trained teacher model or an ensemble of teacher models.

In this paper, anchoring on the computational capabilities of an Edge device, NVIDIA Jetson Nano, we propose a framework of vehicle counting that follows the detection-tracking-counting (DTC) model. We then use the 2021 AI City Challenge Track 1 [27] evaluation server to validate our counting accuracy and the computational efficiency of our model aligning with the goal of the AI City Challenge 2021's Track 1 to develop class-wise, motion-specific vehicle counting systems that can efficiently record vehicles in two categories, i.e., cars and trucks, in different traffic paths and scenes in real-time on a single-board computer.

Our contributions to the paper are the following:

- We improve the generalization of Tiny YOLO [29] by using an ensemble Knowledge Distillation technique [2] consisting of 3 different state-of-the-art object detection networks, thereby improving its detection ac-

curacy. Since Tiny YOLO is already lightweight, enhancing its detection accuracy will result in a better speed-accuracy tradeoff.

- In traffic scenes, when the vehicle density is high, motions usually accompany sudden changes in velocity and positions. We modify the tracker code and use an improved Kalman Filter model to circumvent these problems. We avoid using Deep Learning-based Trackers since they are computationally expensive.

- Finally, we compare our method on popular object detection datasets and use the AI City Challenge's evaluation server to validate our counts. Our experiments suggest that this implementation increases resource usage efficiency on an IoT device and effectively leverages a reasonably accurate DTC approach to traffic volume counting.

This is the first study, to the best of our knowledge, that uses ensemble knowledge distillation for object detection. We empirically validate the performance improvement produced when using this approach on the traffic domain by running extensive experiments on popular datasets [9, 22, 26].

2. Related Works

2.1. Object Detection

Object Detection is a task of computer vision to localize and classify objects. Object detection can be instrumental in vehicle identification [30], anomaly detection [28], lane identification [3], and pothole detection [10–12]. The research community has shifted its attention to deep learning to tackle the object detection problem in the past decade. Research results have indisputably demonstrated the effectiveness of deep neural networks (DNN) for accurately recognizing image objects [5]. However, the improvement in accuracy has reduced computation speed even with high-end machines [21]. Thus, we need model compression techniques to scale these models on edge devices [6, 20, 32, 33].

2.2. Knowledge Distillation

Knowledge distillation refers to the process of transferring the knowledge from a large, unwieldy model or set of models to a single smaller model that can be practically deployed under real-world constraints [16]. Knowledge Distillation is a popular technique for image classification [7].

This method can also be used as a model compression technique for object detection. However, in the case of object detection, multiple models differ significantly. For example, YOLO is a single-shot object detector, whereas Faster RCNN is a two-stage network. Therefore, distilling the layers of these networks together becomes an arduous task. Researchers use similar teacher and student models for the knowledge distillation process [13, 24, 37]. However, restricting to similar models limits the scope of performance improvement.

3. Proposed Vehicle Counting Framework

As shown in Fig. 1, the full pipeline can be divided into two stages:

- Training Phase
- Inference Phase

3.1. Training the Student Network

We train the Tiny YOLO architecture (student network) with an ensemble of multiple teachers, such as Faster RCNN, SSD, and YOLO. The student network is first initialized with Imagenet weights. During the entire training phase, the weights of the teacher networks are frozen. Then, for each batch, the teachers' predicted outputs are reshaped to a feature map of size 26×26, and the mean feature map of all the teachers is computed. While training the student, we use this mean feature map as the reference feature map for the student network along with a non-local module [38], which is an effective method to improve the performance of neural networks by capturing the global relation information [35]. Here, we apply the non-local module to capture the relation between pixels in an image. The loss function of the student network ($\mathcal{L}_s(z)$) is given by the following expression:

$$\mathcal{L}_s = \mathcal{L}_{sc} + \mathcal{L}_{so} + \mathcal{L}_{scl} + \mathcal{L}_{sYOLO} + \mathcal{L}_2(t, s) + \mathcal{L}_2(r^t, r^s)$$

- $\mathcal{L}_{sc}$ is the coordinate loss of the Tiny YOLO network. This loss checks if the object is covered entirely by the bounding box.

- $\mathcal{L}_{so}$ is the objectness loss of the Tiny YOLO network. This loss accounts for the box-object Intersection of Union (IoU) prediction.

- $\mathcal{L}_{scl}$ is the classification loss of the Tiny YOLO network. This is '1' for the correct classes and '0' for all the other classes for the object in a box.

- $\mathcal{L}_{sYOLO}$ is the special YOLO loss, which captures the deviation of the anchor box generated from its original anchor shape and location.

- $\mathcal{L}_2(t, s)$ is the $\mathcal{L}_2$ norm of the mean feature map of the teachers and the feature map of the student network.

- $\mathcal{L}_2(r^t, r^s)$ is the $\mathcal{L}_2$ norm of the obtained relational information of the teacher (mean relational information of all the teachers) and student network.

  After the student model is fully trained, it is further optimized using the Tensor RT module [17] to make the model more lightweight.

3.2. Estimating the Vehicle Counts

The trained student model is loaded into the edge device. We then use the standard Simple Online Real-time Tracker (SORT) [36] to estimate the vehicle's trajectories. The Kalman filter is a crucial component in SORT. Our state contains 8 variables; $(u, v, a, h, u', v', a', h')$ where (u, v) are centres of the bounding boxes, a is the aspect ratio and h, the height of the image. The other variables are the respective velocities of the variables.

We create a "Track" for each detection with all the necessary state information. We also have a parameter to track and delete tracks that had their last successful detection long back, as those objects would have left the scene. Also, there is a minimum number of detections threshold for the first few frames to eliminate duplicate tracks. Then, we use the Hungarian Algorithm [18] to assign IDs for the various tracks. These IDs are used to update the classified count of the vehicles.

4. Implementation Details

We ran our experiments on 3 standard object detection datasets, namely: Pascal VOC, IITM-Hetra, and COCO. No data augmentation was performed for Pascal VOC and COCO datasets. IITM-Hetra was augmented with Pascal VOC 2007 to improve the performance as the number of samples in IITM-Hetra was insufficient, even for the teacher networks. The vehicle detection training was performed in a GPU Cluster, having several GPU Machines like NVIDIA Titan X, NVIDIA 1080Ti, and NVIDIA DGX with GPU RAM sizes 12Gi, 11Gi, and 32Gi, respectively. We used the pre-trained teacher models (YOLOv3, Faster RCNN, and SSD) with the input size fixed to 416×416 and initialized the student network with Imagenet weights. The student model was trained for 100 epochs, with a batch size of 32. Adam was applied as the optimizer, and we decayed the initial learning rate from $3.5e^{-4}$ to $7.7e^{-7}$ using a cosine annealing scheduler and the decay parameter was set to e^{-1}. The inference was run on an edge device, **NVIDIA Jetson Nano**, which is a 128-core Maxwell, Quad-core ARM $A57$ @ 1.43 GHz processor with a 4Gi RAM.

5. Experiments and Results

For all the experiments, we use the Mean Average Precision (MAP) score and the average recall (AR) score as the metrics to compare.

5.1. Vehicle Detection

We experimented with multiple knowledge distillation setups to train the student network and compared the results with the vanilla Tiny YOLO architecture with no distillation. The baseline model was initialized with Imagenet weights and is trained on the various datasets.

1. Using YOLOv3 as the teacher network and applying distillation on feature map layers.

2. Using two teacher networks - YOLOv3 and YOLOv2, for the multiple layer setup. We chose the best-performing teacher for a batch.

3. Using 3 teachers (Faster RCNN, YOLOv3, and SSD), averaging the feature maps of the teachers and using them to train the student network.

The teacher models are very accurate in all the datasets and their mean mAP score is 0.74, while the mean AR score is 0.87.

Dataset	Model	mAP	AR
COCO	Tiny YOLO (Baseline) (No Distillation)	0.237	0.35
COCO	Tiny YOLO (Distilling multiple layers)	**0.241**	0.35
Pascal VOC 2012	Tiny YOLO (Baseline) (No Distillation)	0.31	0.42
Pascal VOC 2012	Tiny YOLO (Distilling multiple layers)	**0.33**	**0.44**
IITM-Hetra	Tiny YOLO (Baseline) (No Distillation)	0.32	0.41
IITM-Hetra	Tiny YOLO (Distilling multiple layers)	0.32	**0.412**

Table 1. Distilling multiple layers of a single teacher

Dataset	Model	mAP	AR
COCO	Tiny YOLO (Baseline) (No Distillation)	0.237	0.35
COCO	Tiny YOLO (2 Teachers, multiple layers)	**0.254**	0.356
Pascal VOC 2012	Tiny YOLO (Baseline) (No Distillation)	0.31	0.42
Pascal VOC 2012	Tiny YOLO (2 Teachers, multiple layers)	**0.35**	**0.45**
IITM-Hetra	Tiny YOLO (Baseline) (No Distillation)	**0.32**	0.41
IITM-Hetra	Tiny YOLO (2 Teachers, multiple layers)	0.31	**0.42**

Table 2. Distilling multiple layers of 2 Teachers

Dataset	Model	mAP	AR
COCO	Tiny YOLO (Baseline) (No Distillation)	0.237	0.35
COCO	Tiny YOLO (Multiple teachers)	**0.28**	**0.41**
Pascal VOC 2012	Tiny YOLO (Baseline) (No Distillation)	0.31	0.42
Pascal VOC 2012	Tiny YOLO (Multiple teachers)	**0.41**	**0.53**
IITM-Hetra	Tiny YOLO (Baseline) (No Distillation)	0.32	0.41
IITM-Hetra	Tiny YOLO (Multiple teachers)	**0.39**	**0.58**

Table 3. Distilling multiple Teachers

In Tables 1 and 2, we notice a slight improvement in the mAP scores and AR scores of the distilled models. These improvements, however, are not very significant. In Table 3, the increase in performance is evident. This could be because of incorporating multiple different teacher networks for knowledge distillation.

5.1.1 Visualizing the detection of the student network

We have visualized the predictions of the student model on various datasets and compared them with the baselines.

(a) Tiny YOLO Baseline (No distillation)

(b) Our model (Distilled from multiple teachers)

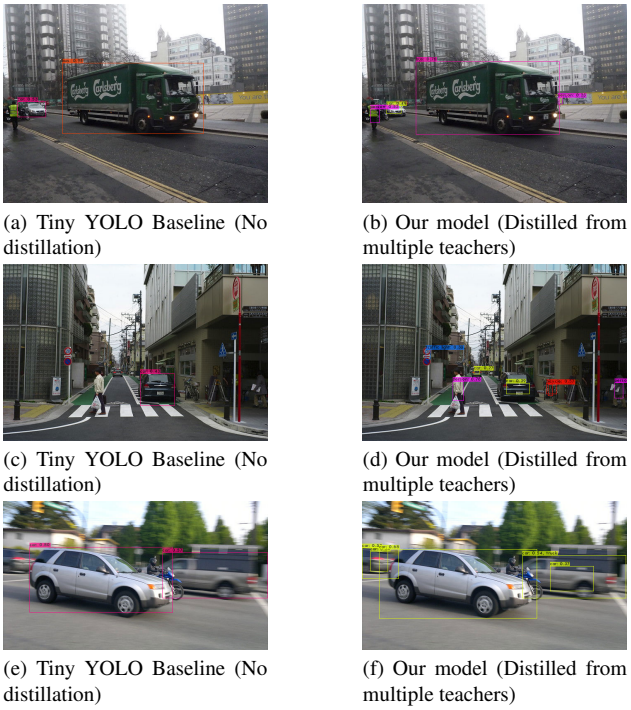
(c) Tiny YOLO Baseline (No distillation)

(d) Our model (Distilled from multiple teachers)

(e) Tiny YOLO Baseline (No distillation)

(f) Our model (Distilled from multiple teachers)

Figure 2. Vehicle Detection on Pascal VOC Dataset



(a) Tiny YOLO Baseline (No distillation)

(b) Our model (Distilled from multiple teachers)

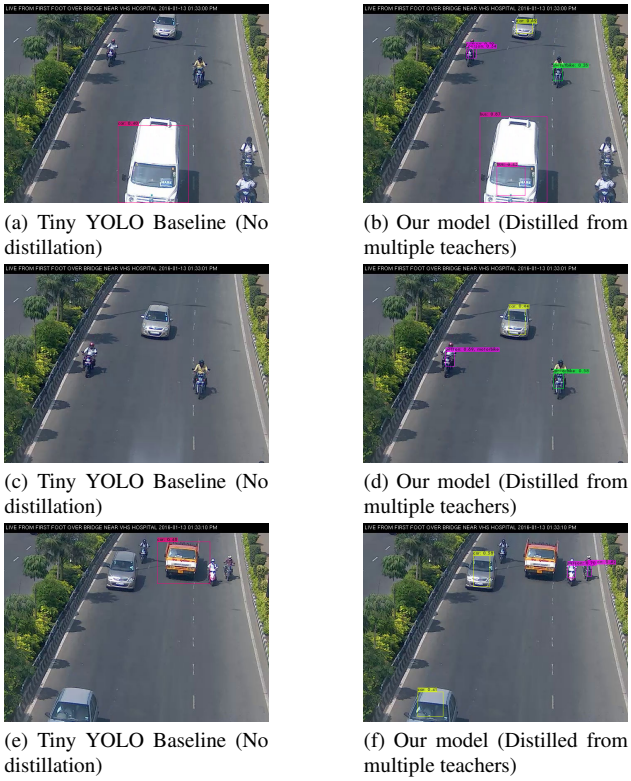
(c) Tiny YOLO Baseline (No distillation)

(d) Our model (Distilled from multiple teachers)

(e) Tiny YOLO Baseline (No distillation)

(f) Our model (Distilled from multiple teachers)

Figure 3. Vehicle Detection on COCO Dataset



(a) Tiny YOLO Baseline (No distillation)

(b) Our model (Distilled from multiple teachers)

(c) Tiny YOLO Baseline (No distillation)

(d) Our model (Distilled from multiple teachers)

(e) Tiny YOLO Baseline (No distillation)

(f) Our model (Distilled from multiple teachers)

Figure 4. Vehicle Detection on IITM-Hetra Dataset

Our proposed approach performs better than the vanilla Tiny YOLO network in many instances. The baseline Tiny YOLO model fails to detect efficiently in the complex examples like Figure 2e, where the baseline predicted a truck and car. As seen in Figure 2b, our proposed model is able to identify a lot more objects in the frame. However, there are overlapping detections, and these could be post-processed. There are instances where the vanilla Tiny YOLO architecture failed to return a single prediction (Ex: Figure 4c) in the IITM-Hetra dataset.

5.2. Vehicle Counting

The student model trained on IITM-Hetra and the YOLOv3 model trained on COCO are evaluated on the AI City Challenge 2021's Track 1 server to get the count accuracy. [27]

The metric used is the $S1$ score, which is defined as $S1 = 0.3 * S1_{Efficiency} + 0.7 * S1_{Effectiveness}$, where $S_{Efficiency}$ is calculated based on the execution time and is adjusted by the Base Factor which is dependent on the running system's CPU and GPU computation.

It assesses the solution's ability to execute online within its computing environment and resources. On the other hand, $S_{Effectiveness}$ is computed for vehicle counts as a weighted average of normalized weighted root mean square error scores (nwRMSE) across all videos, movements, and

vehicle classes of the test sets.

Model	$S1_{Effectiveness}$	$S1_{Efficiency}$	S1
YOLOv3 (Teacher)	0.9425	0.9911	0.9571
Tiny YOLO (Distilled) (Student)	0.5840	0.9995	0.7085

Table 4. Counting Accuracy

6. Conclusion

In this paper, we have presented a low-compute framework to estimate the traffic counts. Our solution consists of a fast object detector (Tiny YOLO) trained using Knowledge Distillation from 3 teacher networks (Faster RCNN, YOLOv3, and SSD), Tensor-RT Optimization of the learned model, and estimating the count of the traffic using the SORT Algorithm in real-time on edge devices. Both the Effectiveness and Efficiency of our solution are experimentally illustrated using multiple data sources. Based on the results, there is a significant potential for generalizing tiny models and improving performance.

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