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Comparative Study of Vehicle Detection using SSD and Faster RCNN

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Abstract— With the recent developments in Artificial Intelligence, vehicle detection systems have become an essential part of many sectors like transport, automobile, security, law enforcement, and traffic management. This increased the requirement for an efficient system for vehicle detection. The main focus of our work is to find the best algorithm which can be used to design a vehicle detection system. For this, we compare two well-known deep learning algorithms which are Faster R-CNN and Single Shot Detector (SSD) algorithms. Both of the Pre-trained models of Tensorflow were tested on a dataset of hundred images with cars in them. It was found that Faster R-CNN is better with an accuracy score of 82.75 but was slower than SSD, whereas SSD had an accuracy score of 80.58 but was faster compared to Faster R-CNN.

Index Terms— Deep learning algorithms, Faster RCNN, Pre-trained Models, SSD, Traffic Management, Tensorflow, Vehicle Detection

1. INTRODUCTION:

For many centuries, vehicles and transportation were a part of human society and they played a substantial role in the day-to-day lives of people. It might be said that humankind won't be there where it is currently if there were no vehicles or methods for transportation. With the invention of automobiles, the transportation industry started blooming and the trade became faster which led to the faster development of the world we are living in now. Common people also started to own automobiles for movement and transport.

The improvement in information technology and artificial intelligence has been expanding since the start of the 21st century as a result of broad research and the increment in the requirement for automation. Practically every industry on the planet currently uses automation which is built with the help of artificial intelligence. The automobile sector likewise employed many new technologies which have brought many changes in manufacturing and the usage of vehicles by many people and industries from goods trade to daily commute. Consequently, there had been a gigantic increase in the requirement for automation in this area as well. This led to the upgrade of the vehicles which we use every day. Autonomous vehicles are designed in such a way that they can proceed onward the road without the necessity of manual driving.

The key technology which helps the autonomous car to move on the road is vehicle detection. Since the research began on vehicle detection, the autonomous vehicle industry started to bloom and began using these systems in their design.

This technology is also heavily used for other purposes like traffic management, vehicle security, law enforcement, etc. Thus the designed system must be of the highest accuracy. Many vehicle detection systems were designed based on various algorithms.

The main aim of our research is to discover the best algorithm which can be used to develop a vehicle detection system. For this, we compare two well-known algorithms, Faster RCNN and Single Shot Detection (SDT) algorithms. We use two pre-trained models and test them on hundred images of cars. The testing dataset is a labelled one and the results of the models are compared with the original values which will let us recognize which one is best suitable for vehicle detection system design.

1.1 Deep Learning based Vehicle Detection Algorithms

Due to the increase in demand for real-time object detection in the last few years, deep learning object detection algorithms had been developed in two directions, two stage object detection algorithms which give importance to accuracy and one stage object detection algorithms which give importance to detection speed.

1.1.1 Two Stage Vehicle Detection Algorithms:

Two-stage vehicle detection algorithms make a model to use a Region Proposal Network (RPN) to generate regions of interests in the first step and send the region proposals for object classification and bounding-box regression. Some examples of two-stage vehicle detection algorithms are R-CNN, Fast R-CNN, Faster R-CNN.

1.1.2 One Stage Vehicle Detection Algorithms:

One stage vehicle detection algorithms make a model to detect all bounding boxes in a single pass. These algorithms do not include the region proposal stage. Some examples of one-stage vehicle detection algorithms are SSD, YOLO, YOLOV2, YOLOV3.

Our work only focuses on Faster R-CNN and SSD algorithms.

1.2 TensorFlow Pre-Trained Models

Object detection problems can be solved by using the TensorFlow framework. Tensorflow Model Zoo consists of pretrained models. These models are trained using the images of COCO Dataset, KITTI Dataset, and Open Images Dataset.

We are using Faster RCNN ResNet50 and SSD MobileNet models, which are trained on COCO Dataset.

1.2.1 Faster R-CNN ResNet50

The architecture of Faster R-CNN uses a separate network to find the region proposals i.e., Region Proposal Network (RPN). RPN is used to find out the area where the object is found, the founded area is labeled as a foreground class.

The RPN produces feature maps with various sizes as the output. Region of interest pooling (ROI) takes these feature maps as input. The ROI will reduce the various sizes of feature maps into same size feature maps by using the Max-Pooling Method.

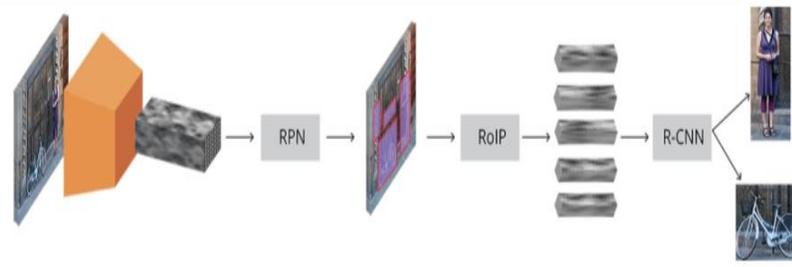


Figure 1: Faster RCNN Architecture

This network was an improved algorithm based on ResNet-50 [1] network, and its detection accuracy was higher in range because it detects small objects.

1.2.2 SSD MobileNet

SSD is a popular algorithm in Object detection considered as state-of-the-art in accuracy. SSD [2] approach produces a set of fixed size bounding boxes. It produces scores for the existence of object class instances in those bounding boxes and these boxes were sent to the non-maximum suppression step which selects the appropriate bounding box for the object.

SSD MobileNet uses MobileNet until the Conv-6 layer, then we will get the output as feature maps. Each feature map is connected to the last recognition layer, which allows the detection and localization of objects of different scales. The advantages of MobileNet are accurate and fast.

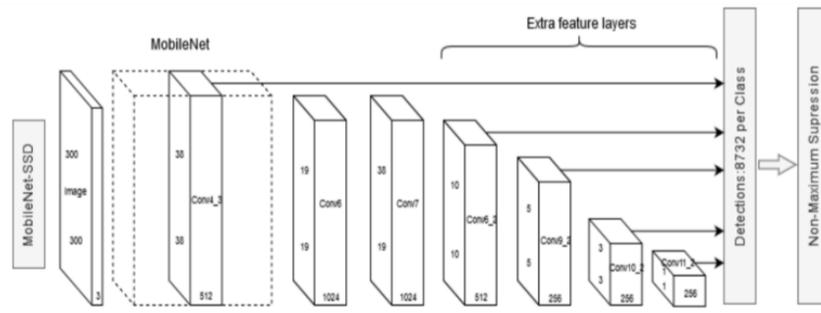


Figure 2: SSD MobileNet Architecture

Following this section are the related work, methodology, and results. We give some concluding remarks in the final section.

2. RELATED WORK:

Many vehicle detection systems were designed using different approaches. The authors in [3] used tiny-YOLOv3 to design a data-driven vehicle detection system. The two-scale detections in tiny-YOLOv3 were increased to three by using context feature information. A spatial pyramid pooling (SPP) module and K-means clustering were used to further improve the existing module. When tested on the KITTY dataset the efficiency of their model was found to be 91.03% and the frame rate was increased to 144 frames per second (fps) which is more than the optimal rate for real-time systems. Generally, the models built on Deep Convolutional Neural Networks (DCNN) used in vehicle detection require hardware with large computing power, huge disc space, and RAM. Without such hardware configurations, the system might not run quickly and accurately in traffic conditions and hence those detectors are not used. The authors in [4] overcame this problem by proposing a novel algorithm based on DenseLightNet which not only uses a lighter network but also improves speed without the need for high-performing hardware.

Their model was three times faster and also smaller than YoloV3.

The authors in [5] designed a moving vehicle detection system based on an artificial neural network (ANN) and oppositional gravitational search optimization algorithm (ANN–OGSA). The system first generates the background for the vehicle, followed by the vehicle detection by the algorithm. The oppositional gravitational search optimization helps in optimal weight selection for the ANN. The efficiency of their method was 3% more than the normal Gravitational Search Optimization Artificial Neural Network (GSA-ANN) algorithm and 6% more than traditional Artificial Neural Networks. Though they are quick and accurate, the SSDMultibox detector does not perform well for images with high resolution. To overcome this problem, a new CNN framework based on SSD and integrated with the feature fusion and detection modules was put forward by the authors of [6]. An average precision of 0.904 was obtained which is higher than that of SSD512 but with the same speed even when normalization layers were embedded inside the network.

3. WORKING:

All the models are loaded and the condition, if the model is not present, is handled by downloading the model from TensorFlow COCO Zoo is automated in the script. To evaluate the model, we used a part of the huge dataset containing 100 images. Its Ground True values i.e., bounding boxes of the vehicles in the image are gathered in a CSV file.

The image is read using OpenCV and it is converted into the tensor data type. The model is already loaded in `detection_model` and the preprocessing method is used to detect in the input image tensor. The detections and their respective bounding boxes are stored in dictionaries. We then compare the ground true bounding box with the predicted bounding box of each detection in the image. For all the detections in each image, True Positive, True Negative, False Positive, and False Negatives are calculated. Using these values recall, precision and accuracy are measured.

The same algorithm is used for both the Models i.e., Faster R CNN and SSD MobileNet. The results of each model are saved in pickle files for further visualization of the accuracy and other metrics.

4. RESULTS:

This section shows experimental results obtained by two pre-trained models of tensorflow.100 images were used to evaluate the performance of these pre-trained models. Based on the outputs two models, it is observed that Faster RCNN Resnet50 detects vehicles with high confidence than SSD MobileNet.



Figure 3: Prediction of Faster R-CNN on Sample Image

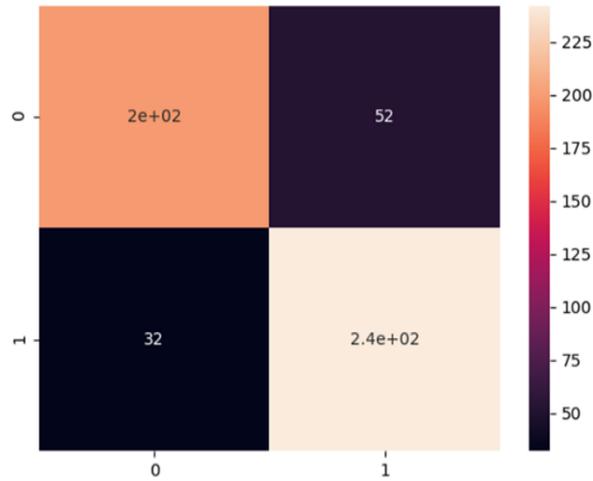


Figure 4: Confusion matrix for Faster RCNN



Figure 5: Prediction of SSD MobileNet on Sample Image

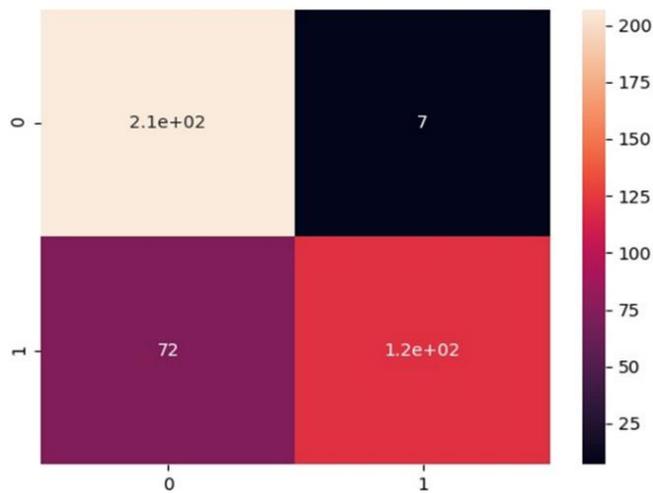


Figure 6: Confusion matrix for SSD MobileNet.

5. CONCLUSION:

Two well-known algorithms which are Faster R-CNN and Single Shot Detector algorithms were compared in terms of efficiency. Two pre-trained models were used and tested on a dataset of hundred images with cars in them. The results showed that the Faster R-CNN model performed better than the SSD network with an accuracy of 82.57 but slower whereas SSD had an accuracy of 80.58 but performed detections quicker. Therefore, it is advisable to develop a vehicle detection system by selecting the appropriate algorithm based on requirements. If accuracy is more important it is recommended to use Faster R-CNN, on the other side, if the speed is required, the SSD algorithm is preferable.

6. FUTURE SCOPE

We used the pre-trained models of Tensorflow for comparing algorithms. This work can be further upgraded by manually training the model on a preferably self-collected dataset or well-known datasets for training in vehicle detection so that the results can be improved.

REFERENCES

- [1]. Yi Xiao, Xinqing Wang, Peng Zhang, Fanjie Meng and Faming Shao "Object Detection Based on Faster R-CNN Algorithm with Skip Pooling and Fusion of Contextual Information".
- [2]. Alexander Driaba, Aleksei Gordeev, Vladimir Klyachin "Recognition of Various Objects from a Certain Categorical Set in Real Time Using Deep Convolutional Neural Networks".
- [3]. X. Wang, S. Wang, J. Cao and Y. Wang, "Data-Driven Based Tiny-YOLOv3 Method for Front Vehicle Detection Inducing SPP-Net," in IEEE Access, vol. 8, pp. 110227-110236, 2020, doi: 10.1109/ACCESS.2020.3001279.
- [4]. L. Chen, Q. Ding, Q. Zou, Z. Chen and L. Li, "DenseLightNet: A Light-Weight Vehicle Detection Network for Autonomous Driving," in IEEE Transactions on Industrial Electronics, vol. 67, no. 12, pp. 10600-10609, Dec. 2020, doi: 10.1109/TIE.2019.2962413.
- [5]. Appathurai, A., Sundarasekar, R., Raja, C. et al. "An Efficient Optimal Neural Network-Based Moving Vehicle Detection in Traffic Video Surveillance System", Circuits Syst Signal Process 39, 734–756 (2020). <https://doi.org/10.1007/s00034-019-01224-9>.
- [6]. Gao, H; X Li. The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences; Gottingen Vol. XLIII-B3-2020,: 49-54. Gottingen: Copernicus GmbH. (2020) DOI:10.5194/isprs-archives-XLIII-B3-2020-49-2020.
- [7]. S. Han, H. Mao, and W. J. Dally. Deep compression: Compressing deep neural network with pruning, trained quantization and Huffman coding. CoRR, abs/1510.00149, 2, 2015. 2.
- [8]. Sadanand Howal, Aishwarya Jadhav, Chandrakirti Arthshi, Sapana Nalavade, and Sonam Shinde: "Object Detection for Autonomous Vehicle Using TensorFlow".
- [9]. Qiaoqian Chen, Na Huang, Jieming Zhou, Zhao Tan: "An SSD Algorithm Based on Vehicle Counting Method". DOI: 10.23919/ChiCC.2018.8483037.
- [10]. Jiaqi Fan, Tianjiao Huo, Xin Li, Ting Qu, Bingzhao Gao, Hong Chen: "Covered Vehicle Detection in Autonomous Driving Based on Faster RCNN". DOI: 10.23919/CCC50068.2020.9189180.
- [11]. Nikhil Yadav, Utkarsh Binay: "Comparative Study of Object Detection Algorithms".
- [12]. Qiong WU, Sheng-bin LIAO: "Single Shot MultiBox Detector for Vehicles and Pedestrians Detections and Classification" DOI: 10.12783/dtetr/apop2017/18705.
- [13]. Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun: "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks".
- [14]. Tiagrajah V. Janahiraman and Mohamed Shahrul Mohamed Subuhan: "Traffic Light Detection Using Tensorflow Object Detection Framework". DOI: 10.1109/ICSEngT.2019.8906486.