VEHICLE DETECTION AND COUNTING IN IMAGES

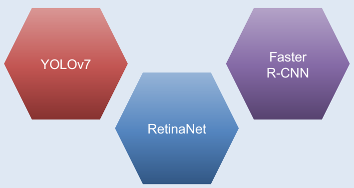
Anurag Hambir Ryan Furtado FNU Himanshu Akash Bhapkar

Indiana University – Luddy School of Informatics, Computing and Engineering

Introduction

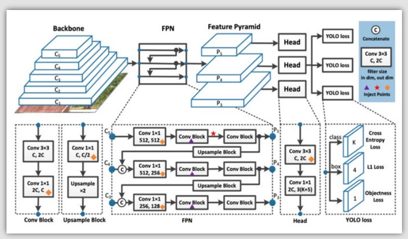
This project is inspired by the problem of heavy traffic observed on streets and highways which tends to be a major problem faced by a lot of metropolitan cities these days especially during holiday periods or during peak work hours. We aim to count the number of vehicles on such roads so that we can take preventive measures to control the flow of traffic by detecting the presence of traffic in real time and suggesting alternative routes to drivers beforehand.

To solve this problem, we will fine-tune some well-known models with pretrained weights on our dataset and compare their performance in order to understand their strengths and weaknesses.



Methodology

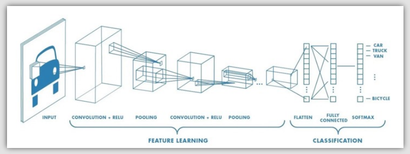
YOLO is a single stage object detection technique based on efficient layer aggregation network (ELAN). ELAN controls the shortest and longest gradient path to make the network efficient thereby allowing deeper networks to be trained easily.



RetinaNet is a single stage object detection technique that extracts features at various scales from an input image using a feature pyramid network, and then utilizes a feature fusion module to fuse the features at various scales. It uses a focal loss function which assigns higher weights to harder examples in order to address the class imbalance problem.

Region Based CNN(R-CNN) is a deep learning two stage object detection algorithm. It has categorization and localization responsibilities as two distinct stages. A list of potential object regions is generated during the first step, along with boxes around the regions.

Next, Convolutional Neural Networks are applied to each region to produce fixed-length feature vectors. The final step is to transmit feature vectors through an object categorization and Non-Maximal suppression layer.



Experiments

- We have used Traffic Image Dataset from Kaggle consisting of around 2700 images of traffic in the country of Bangladesh.
- The dataset contains annotations in the format of text files with bounding boxes. For some of the models this was translated to xml files using the PASCAL_VOC format.
- We used **YOLOv7 (Fixed Resolution and Multi-Resolution)**, **RetinaNet** and **Faster R-CNN** to perform transfer learning in order to fine-tune using the traffic image dataset.
- We also ran different experiments with 10 and 20 epochs which still took a lot of time due to hardware restrictions (Google Colab).
- The test data contains 300 images and calculated Mean Average Precision (mAP) according to different parameters.
- The Mean Average Precision (mAP) is calculated on the correct count of the objects (vehicles) in the test dataset.
- The table below shows the results on each model, with YOLOv7 (Multi-Resolution) performing best for our dataset.

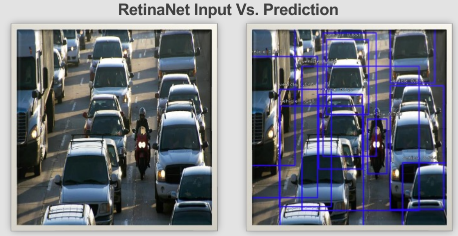
Mean Average Precision (mAP) @ 0.5		
Number Of Epochs	**10**	**20**
YOLOv7 (Fixed Resolution)	0.65	0.72
YOLOv7 (Multi-Resolution)	0.69	0.76
Retina Net	0.37	0.38
Faster R-CNN	0.51	0.55

Results

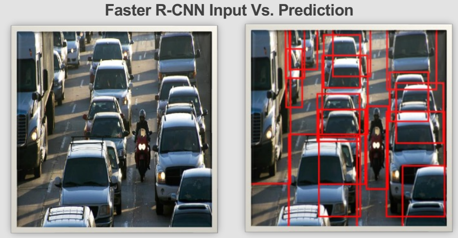
YOLOv7 (Fixed Resolution) Input Vs. Prediction

YOLOv7 (Multi-Resolution) Input Vs. Prediction

RetinaNet Input Vs. Prediction



Faster R-CNN Input Vs. Prediction



Conclusion

Based on our experiments using the traffic dataset we conclude that Yolov7 is the fastest and the most accurate out of the three models, especially the Multi-Resolution variant although it does take more time to fine-tune since it takes into consideration varying resolutions of images.

Practitioners can use these models in real time traffic detection and suggest alternative routes to avoid traffic congestion and in case of people, avoid overcrowding.

These models were trained on a very small dataset of around 2700 images and yet they gave amazing results. If trained with more data and on better hardware architecture, they will definitely produce results with greater accuracy.

Future Work

- These models can be repurposed to be used on videos for efficient real time predictions giving us a better idea of their performance against each other.
- Distinguishing between different types of vehicles as well as their make and model can also be considered for denser prediction tasks.

References

- Road Vehicle Images Dataset: https://www.kaggle.com/datasets/ashfakyeafi/road-vehicle-images-dataset
- P. Gao, J. Tian, Y. Tai, T. Zhao and Q. Gao, "Vehicle Detection with Bottom Enhanced RetinaNet in Aerial Images," IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, Waikoloa, HI, USA, 2020, pp. 1173-1176, doi: 10.1109/IGARSS39084.2020.9323216.
- P. Gao, J. Tian, Y. Tai, T. Zhao and Q. Gao, "Vehicle Detection with Bottom Enhanced RetinaNet in Aerial Images," IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, Waikoloa, HI, USA, 2020, pp. 1173-1176, doi: 10.1109/IGARSS39084.2020.9323216.
- M. Manana, C. Tu and P. A. Owolawi, "Preprocessed Faster RCNN for Vehicle Detection," 2018 International Conference on Intelligent and Innovative Computing Applications (ICONIC), Mon Tresor, Mauritius, 2018, pp. 1-4, doi: 10.1109/ICONIC.2018.8601243.
- M. V., V. V. R. and N. A., "A Deep Learning RCNN Approach for Vehicle Recognition in Traffic Surveillance System," 2019 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 2019, pp. 0157-0160, doi: 10.1109/ICCSP.2019.8698018.
- Song, H., Liang, H., Li, H. et al. Vision-based vehicle detection and counting system using deep learning in highway scenes. Eur. Transp. Res. Rev. 11, 51 (2019). https://doi.org/10.1186/s12544-019-0390-4
- R. Kejriwal, R. H J, A. Arora and Mohana, "Vehicle Detection and Counting using Deep Learning basedYOLO and Deep SORT Algorithm for Urban Traffic Management System," 2022 First International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), Trichy, India, 2022, pp. 1-6, doi: 10.1109/ICEEICT53079.2022.9768653.