SMU Data Science Review

Volume 2 | Number 1 Article 23

2019

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Self-Driving Cars: Evaluation of Deep Learning Techniques for Object Detection in Different Driving Conditions

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Abstract. Deep Learning has revolutionized Computer Vision, and it is the core technology behind capabilities of a self-driving car. Convolutional Neural Networks (CNNs) are at the heart of this deep learning revolution for improving the task of object detection. A number of successful object detection systems have been proposed in recent years that are based on CNNs. In this paper, an empirical evaluation of three recent meta-architectures: SSD (Single Shot multi-box Detector), R-CNN (Region-based CNN) and R-FCN (Region-based Fully Convolutional Networks) was conducted to measure how fast and accurate they are in identifying objects on the road, such as vehicles, pedestrians, traffic lights, etc. under four different driving conditions: day, night, rainy and snowy for four different image widths: 150, 300, 450 and 600. The results show that region-based algorithms have higher accuracy with lower inference times for all driving conditions and image sizes. The second principle contribution of this paper is to show that Transfer Learning can be an effective paradigm in improving the performance of these pre-trained networks. With Transfer Learning, we were able to improve the accuracy for rainy and night conditions and achieve less than 2 seconds per image inference time for all conditions, which outperformed the pre-trained networks.

1 Introduction

Computer Vision has become increasingly important and effective in recent years due to its wide-ranging applications in areas as diverse as smart surveillance and monitoring, health and medicine, sports and recreation, robotics, drones, and self-driving cars. Visual recognition tasks, such as image classification, localization, and detection, are the core building blocks of many of these applications and recent developments in Convolutional Neural Networks (CNNs) have led to outstanding performance in these state-of-the-art visual recognition tasks and systems. CNNs are primarily used for image classification tasks, such as, looking at an image and classifying the object in it.

In contrast, the term object localization refers to the task of identifying the location of an object in the image. An object localization algorithm will output the coordinates of the location of an object with respect to the image. In computer vision, the most popular way to localize an object in an image is to represent its location with the help of bounding boxes. The task of object detection combines both classification and localization to identify multiple objects in an image and locate each object within the image. A well-known application of multiple object detection is in self-driving cars, where the algorithm not only needs to detect the cars but also pedestrians, motorcycles, trees and other objects in the frame and then draw bounding boxes around each of the detected objects as shown in Figure 1.

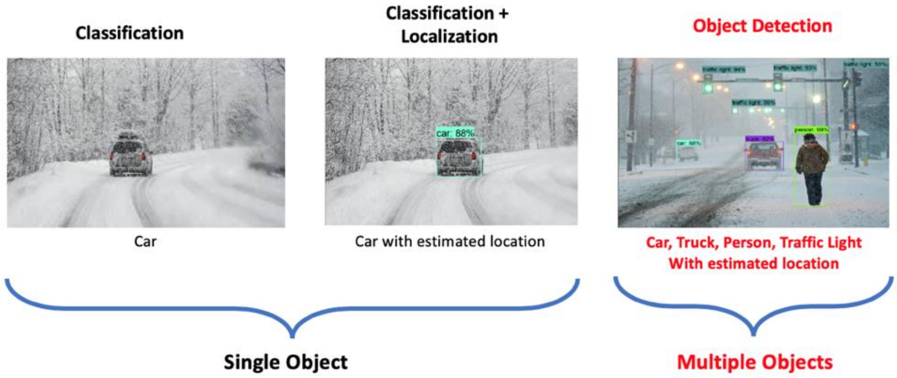

Fig. 1. Distinction between Classification, Localization and Object Detection. A self-driving car employs multiple object detection to classify and localize objects on the road.

Recent advances in self-driving cars have prompted researchers to build a variety of object detection algorithms. Most of these object detection algorithms are based on three meta-architectures: Single Shot multi-box Detector (SSD), Faster R-CNN (Regions with Convolutional Neural Networks) and Region-based Fully Convolutional Networks (R-FCN). Each of these architectures fundamentally differs in the way they build their object detection pipelines. A typical object detection pipeline can be mainly divided into three stages: informative region selection, feature extraction, and classification. This choice gives rise to many combinations of feature extractors and region selection techniques. With these differences, it can be difficult for practitioners to decide what architecture is best suited to their applications.

The goal of this research is to conduct an empirical evaluation of these object detection algorithms in the context of self-driving cars under different driving conditions: day, night, rainy and snowy as shown in Figure 2. This research seeks to provide practitioners with useful insights as to how each of these algorithms performs under different driving conditions. Two key metrics: *mean average precision* (mAP) and *inference time* are used to evaluate these algorithms. The mAP provides a single number summary of how well the object detector performed in detecting and classifying the objects. Inference time measures the speed of detection.

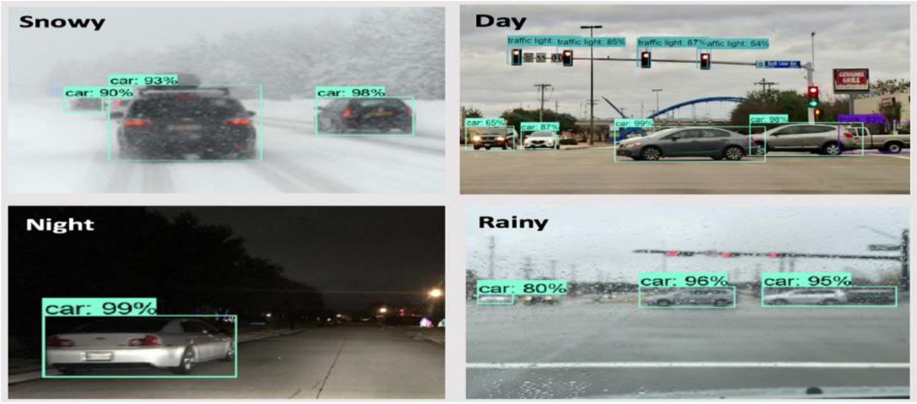

Fig. 2. Object detection under four different driving conditions: Snowy, Day, Night and Rainy.

A key challenge with object detection is that labeled data is scarce and it takes substantial effort to gather and annotate each image to be used in the training phase. Moreover, training an object detector from scratch takes a significant amount of time and compute resources. To overcome this problem, pre-trained object detection models trained on *Common Objects in Context (COCO)* dataset were used, and transfer learning was applied by fine-tuning the deeper layers in the network with labeled image data of vehicles in different driving conditions.

2 Background

2.1 Convolutional Neural Networks

Detection and recognition of objects in the observed scenes is a natural biological ability. People and animals perform this effortlessly in daily life to move without collisions, to find food, avoid threats, drive vehicles and so on. However, similar computer methods and algorithms for scene analysis are not so straightforward, despite their unprecedented development. Nevertheless, biological systems after close observations and analysis provide some hints for their machine realizations.

The best example of this is Convolutional Neural Networks (CNNs or ConvNets) that are inspired by the biological structure of a visual cortex, which contains arrangements of simple and complex cells. These cells are found to activate based on the sub-regions of a visual field. These sub-regions are called receptive fields. Inspired from the findings of Hubel et al. study [1], the neurons in a convolutional layer connect to the sub-regions of the layers before that layer instead of being fully-connected as in other types of neural networks. The neurons are unresponsive to the areas outside of these sub-regions in the image. These sub-regions might overlap; hence the neurons of a ConvNet produce spatially-correlated outcomes, whereas, in other types of neural networks, the neurons do not share any connections and produce independent outcomes. Besides, in a neural network with fully-connected neurons, the number of parameters (weights) can increase quickly as the size of the input increases. A convolutional neural network reduces the number of parameters with a reduced number of connections, shared weights, and down-sampling.

Further work determined that the visual cortex is organized in layers. Each layer is responsible for building on the features detected in the previous layers – from lines to contours, to shapes, to entire objects. Furthermore, within a layer of the visual cortex, the same feature detectors were replicated over the whole area in order to detect features in all parts of an image. These ideas significantly impacted the design of convolutional neural nets.

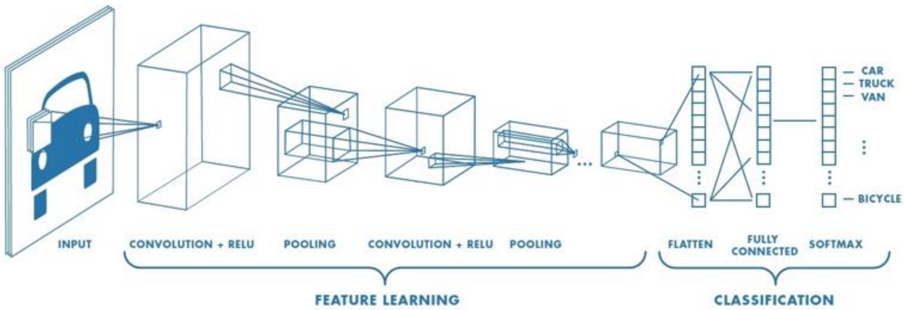

Fig. 3. A ConvNet[1] consists of two stages: *feature learning* and *classification*. The feature learning stage is made up of repeated blocks of convolutional, ReLU and pooling layers and the classification stage consists of one or more fully connected layers ending with a softmax layer.

The basic building blocks of ConvNets (Figure 3) are the convolutional layers, max-pooling or average pooling layers, and fully-connected layers. ConvNets are implemented as a series of interconnected layers. The layers are made up of repeated blocks of convolutional, ReLU (rectified linear units), and pooling layers. The convolutional layers convolve their input with a set of filters. The filters are automatically learned during network training. The ReLU layer adds nonlinearity to the network, which enables the network to learn nonlinear combinations of the original inputs, which is called feature extraction. These learned features, also known as activations, from one layer, become the inputs for the next layer. The pooling layers down-sample their inputs and help consolidate local image features. Finally, the learned features become the inputs to the classifier or the regression function at the end of the network. For image classification problems, the last layer is a classifier, and for object localization problems the last layer is a combination of both.

2.2 CNN architectures

CNN architectures like *ResNet, InceptionV2* are the result of careful experimentation with many architectures and extensive hyperparameter tuning. Many of these architectures have won the ImageNet contest in the recent past. The ImageNet project is a large visual database designed for use in visual object recognition software research. The ImageNet project runs an annual software contest, the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), where software programs compete to classify and detect objects and scenes correctly. Over the last few years, several CNN architectures have won this competition. Most of these CNN architectures follow the same general design principle of successively applying convolutional layers, pooling, and fully connected layers. These architectures serve as rich *feature extractors* which can be used to solve complex computer vision tasks such as, image classification and object detection.

2.3 Computer Vision tasks

Computer Vision is the science of computers and software systems that can recognize and understand images and scenes. As depicted in Figure 4, the three most common tasks in computer vision are image classification, classification with localization and object detection.

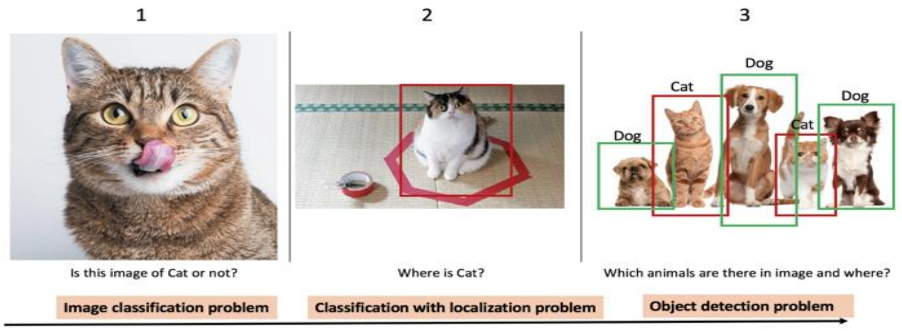

Fig. 4. Three most common Computer vision tasks[2]: classification, classification with localization and object detection.

2.3.1 Image Classification: This is the most common computer vision problem where an algorithm looks at an image and classifies the object in it. Image classification has a wide variety of applications, ranging from face detection on social networks to cancer detection in medicine. Such problems are typically modeled using Convolutional Neural Nets (CNNs). Figure 5 shows the high-level steps involved in a typical image classification task. The input image is sent through multiple convolutional, pooling, non-linear layers and the output of the final layer of the CNN is passed into a softmax layer which converts the numbers between 0 and 1, giving the probability of the image being of a particular class.

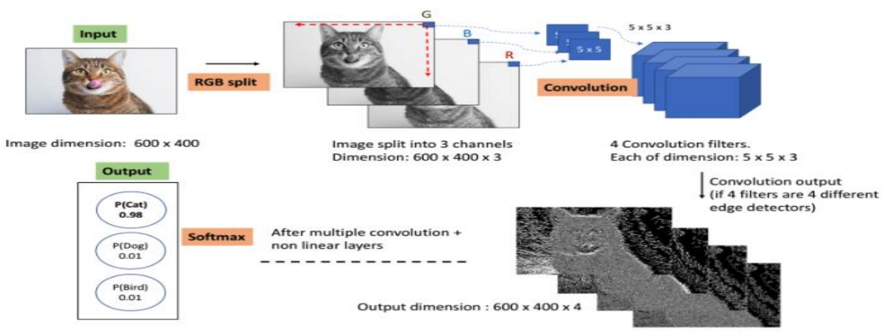

Fig. 5. Steps for image classification using CNN[1]: split the image into three channels; pass it through a series of convolutional, non-linear and pooling layers; feed this into a softmax layer.

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1 https://towardsdatascience.com/evolution-of-object-detection-and-localization-algorithms-e241021d8bad

2.3.2 Object classification and localization: Let us say the goal is not only to know whether there is a cat in the image but where exactly is the cat? Object localization algorithms not only label the class of an object but also draw a bounding box around the position of an object in the image. In order to get the bounding box location, four more numbers are added to the output layer. The final output contains class labels and four numbers to locate the bounding box as shown in Figure 6.

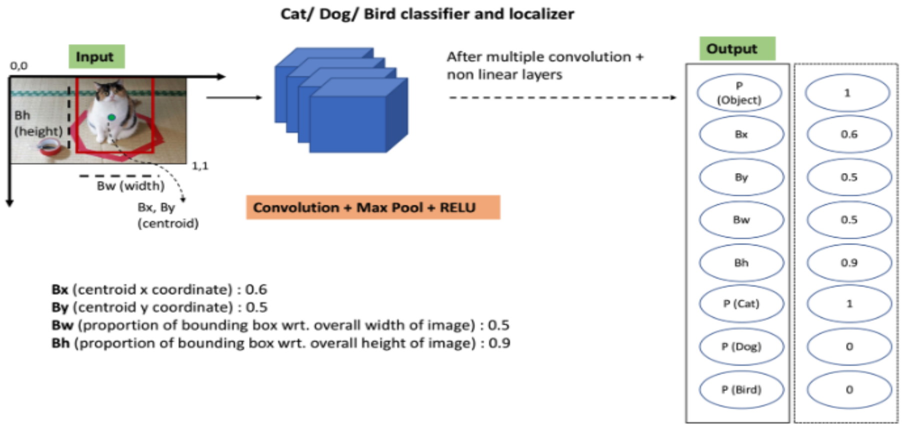

Fig. 6. Input and output for object localization problems[3]: The output contains class labels and bounding box co-ordinates.

2.3.3 Multiple objects detection and localization: What if there are multiple objects in the image (3 dogs and two cats as in Figure 7) and the task is to detect them all? That would be a multiple object detection and localization problem. These kinds of problems need to leverage the ideas or concepts learned from image classification as well as from object localization. For the algorithm to detect all kinds of objects in an image, it needs to be able to classify and localize all the objects in the image. This process is typically done using either a simple sliding window approach, wherein, the cropped window is passed through a ConvNet and have the ConvNet make the predictions. The sliding window is passed through the entire image. In the end, a set of cropped regions will remain, which will have some object, together with class and bounding box of the object. This sliding window approach is a very basic object detection approach, and many advanced object detection algorithms have been devised to tackle this problem. Three meta-architectures are discussed in detail in Section 3.

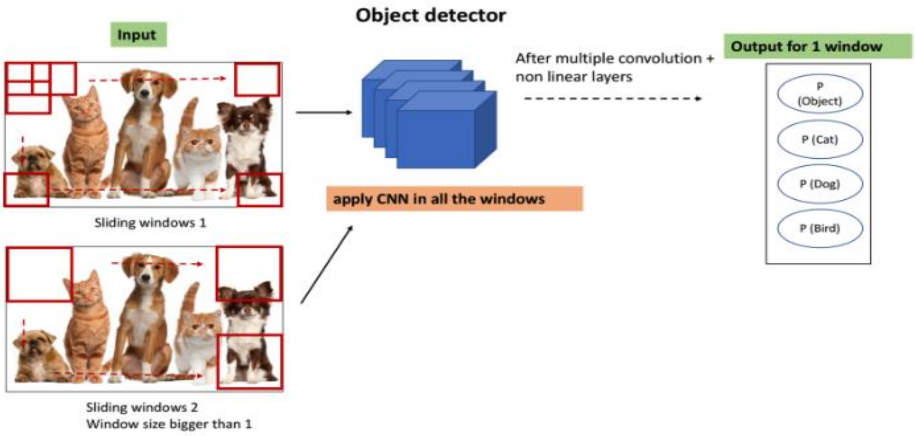

Fig. 7. In multiple object detection problems[2] each sliding window is passed through a CNN and the output contains the probability of an object in addition to the probability of the class.

2.4 Transfer Learning

Transfer learning involves taking a pre-trained neural network and adapting the neural network to a new or different dataset. Depending on the size of the dataset and how similar the data is to the original data set, there are four transfer learning approaches as shown in Figure 8:

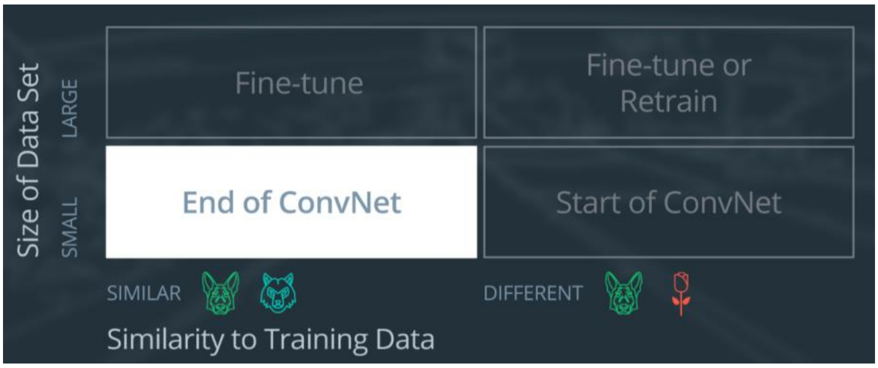

Fig 8. Four types of transfer learning approaches[3]

End of ConvNet: New dataset is *small*, new data is *similar* to original training data.
Start of ConvNet: New dataset is *small*, new data is *different* from original data.
Fine-tune: New data set is *large*, new data is *similar* to original training data.
Fine-tune/retrain: New data set is *large*, new data is *different* from original data.

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[2] https://towardsdatascience.com/evolution-of-object-detection-and-localization-algorithms-e241021d8bad
[3] https://www.udacity.com/course/deep-learning-nanodegree--nd101

Since the data set for this analysis is small and the data is similar to the original training data, the Transfer Learning approach used in this analysis is End of ConvNet. In this approach, the starting layers of the ConvNet are frozen, and only the last few layers are re-trained using the new data. The reason for freezing the starting layers is because these first few layers have already learned the low-level features like edges, shapes, wheels, etc. of the image and thus they do not need to be re-trained again. This same principle is extended to object detection algorithms, where only the last few layers of the meta architecture-based algorithms are re-trained, thus avoiding the need to re-train the entire pipeline, which could take a significant amount of time even using GPUs.

3 Meta-Architectures

State-of-the-art object detection systems are variants of the following approach: hypothesize bounding boxes, resample pixels or features for each box, and apply a high-quality classifier. There are three established classes of methods for object detection in images, one based on sliding windows, the other based on region proposal classification and the last one uses a single forward pass for both object localization and classification tasks.

An intuitive way of localization is to predict several cropped portions of an image with an object. The cropping of the images can be done by moving a window across the image and predicting for every window. The method of moving a smaller window than the image and cropping the image according to window size is called a sliding window. A prediction can be made for every cropped window of the image which is called *sliding window object detection*. The movement of the window has to be uniform across the image. Each portion of the image is passed through the model to find the classification.

There are two problems with this approach: one, it can only find objects that are the same size as the window, that is, the sliding window will miss an object if the object size is bigger than the window size; the second problem is that it is computationally expensive to use a large number of sliding windows. These two issues motivate the need to have advanced methods which are discussed next.

3.1 R-CNN family

As discussed in the earlier sections, object detection is the process of finding and classifying objects in an image. One deep learning approach, regions with convolutional neural networks (R-CNN), combines rectangular and/or square region proposals with convolutional neural network features. Models for object detection using regions with CNNs are based on the following three processes: 1) Find regions in the image that might contain an object. These regions are called region proposals. 2) Extract CNN features from the region proposals. 3) Classify the objects using the extracted features. The Regions based R-CNN family of object detectors uses region proposals to detect objects within images. The number of proposed regions dictates the time it takes to detect objects in an image. The Fast R-CNN and Faster R-CNN detectors are designed to improve detection performance with a large number of regions.

Region Proposal Network (RPN) ranks region on boxes, referred to as anchors, and proposes the ones most likely containing objects. RPN predicts the possibility on an anchor being background or foreground. The output of an RPN is a bunch of boxes/proposals that will be examined by a classifier and regressor, to check the occurrence of objects eventually. The overall loss of the RPN is a combination of the classification loss and the regression loss.

Non-max suppression method is used at the end of the network to discard a large number of predicted boxes based on higher Intersection over Union (IoU) threshold (larger overlapping) and with the highest prediction of the probability of an object existence – and merge highly overlapping bounding boxes.

After RPN, the network yields proposed regions with different sizes, means different sized CNN feature maps. To simplify the differently sized feature maps into the same size, Regions of Interest (ROI) Pooling is used, by reducing the regression output to a fixed size output regardless of input size.

There are three variants of an R-CNN. Each variant attempt to optimize, speed up or enhance the results of one or more of these processes.

3.1.1 R-CNN. The R-CNN detector introduced by Girshick etal.[2] first generates region proposals using an algorithm such as Edge Boxes [3]. The proposal regions are cropped out of the image and resized. Then, the CNN classifies the cropped and resized regions. Finally, the region proposal bounding boxes are refined by a support vector machine (SVM) that is trained using CNN features as shown in Figure 9.

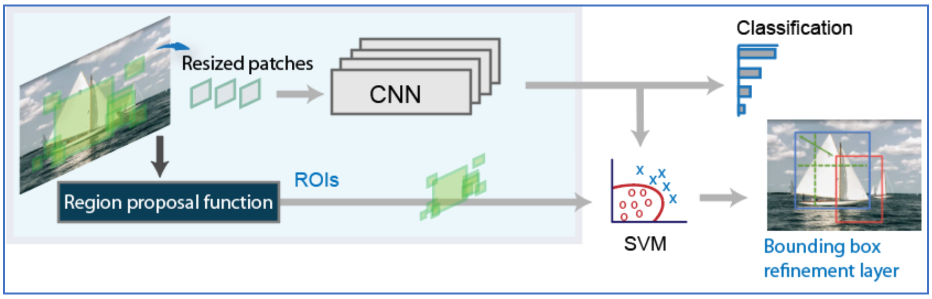


Fig. 9. R-CNN architecture[4] combines rectangular region proposals with CNN features. R-CNN is a two-stage detection algorithm. The first stage identifies a subset of regions in an image that might contain an object. The second stage classifies the object in each region.

R-CNN Selective search proposed ~2000 region candidates for every image which generated CNN feature vector for each image region (N images *2000) making R-CNN very slow and computationally very expensive.

[4] https://www.mathworks.com/help/vision/ug/faster-r-cnn-basics.html

3.1.2 Fast R-CNN. As in the R-CNN detector [2], the Fast R-CNN [4] detector also uses an algorithm like Edge Boxes to generate region proposals. Unlike the R-CNN detector, which crops and resizes region proposals, the Fast R-CNN detector processes the entire image. Whereas an R-CNN detector must classify each region, Fast R-CNN pools CNN features corresponding to each region proposal as shown in Figure 10. Fast R-CNN is more efficient than R-CNN, because, in the Fast R-CNN detector, the computations for overlapping regions are shared.

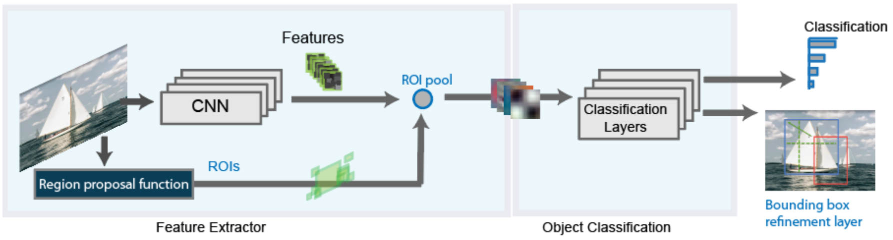


Fig. 10. Fast R-CNN architecture[5]: Unlike the R-CNN detector, which crops and resizes region proposals, the Fast R-CNN detector processes the entire image.

Fast R-CNN is much faster in both training and testing time than the base R-CNN. However, the improvement is not dramatic because the region proposals are generated separately by another model and that is very expensive.

3.1.3 Faster R-CNN. In the Faster R-CNN detector, instead of using an external algorithm like Edge Boxes, Faster R-CNN adds a region proposal network (RPN) to generate region proposals directly in the network (Figure 11). Generating region proposals in the network is faster and better tuned to the input data.

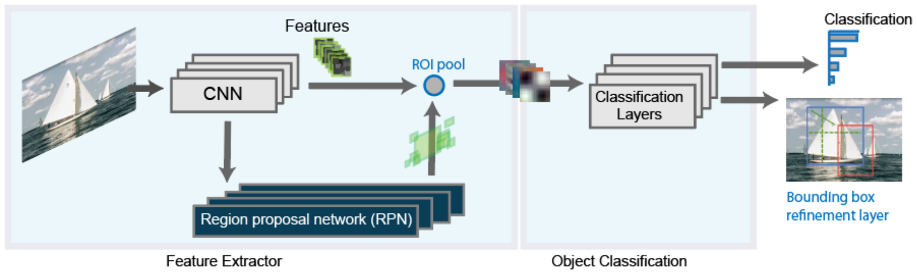


Fig. 11 Faster R-CNN[5]: Instead of using an external algorithm like Edge Boxes, Faster R-CNN adds a region proposal network (RPN) to generate region proposals directly in the network.

In this paper, pre-trained models using Faster R-CNN are used to leverage optimal and accurate regional proposal generation. This aids to improve regional proposal quality of the networks and overall object detection accuracy in an image

[5] https://www.mathworks.com/help/vision/ug/faster-r-cnn-basics.html

3.2 Region-Based Fully Convolutional (R-FCN)

Region-based Fully convolutional networks (R-FCN) introduced by Dai, et al. [5] provides an accurate and efficient object detection. R-FCN closely resembles the architecture of Faster R-CNN, but instead of cropping features from the same layer where region proposals (RoI) are predicted, crops are taken from the last layer of features prior to prediction. See Figure 12. Dai et al. argues, this approach of pushing the cropping to the last layer greatly minimizes the amount of per-region computation that must be performed. Dai et al. showed that the R-FCN model (using Resnet 101) could achieve comparable accuracy to Faster R-CNN often at faster running times [5].

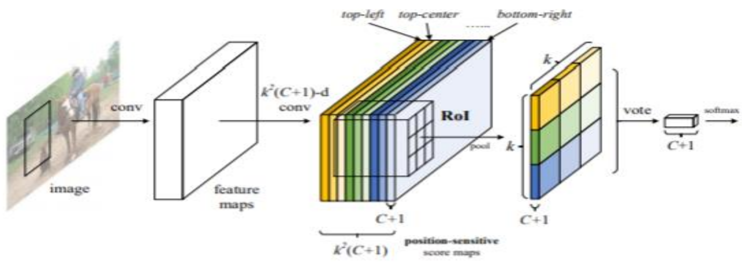


Fig. 12. Overall architecture of R-FCN [9].

In R-FCN architecture above, a given input object is divided into feature maps each detecting the corresponding region of the object. The feature maps are also known as position-sensitive score maps. Taking the example of the 3 X 3 ROI in Figure 12 above, we ask ourselves how likely each in the 3 X 3 matrix contains the corresponding part of the object and assign a score to it. This process of mapping score maps and ROIs to the vote array is called *position-sensitive ROI-pool*. The average of the resulting ROI pool gives the class score for a given object in the given ROI as shown in Figure 13 below.

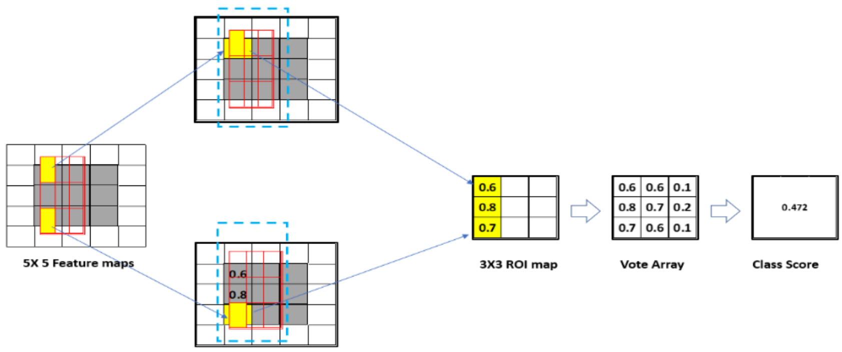


Fig. 13. Applying ROI onto the feature maps to output a 3 x 3 Vote array.

3.3 Single-Shot Detector (SSD)

The term *single shot* means that the tasks of object localization and classification are handled in a single forward pass of the network. It is simple relative to methods that require object proposals because it eliminates proposal generation and subsequent pixel or feature resampling stages and encapsulates all computation in a single network. The SSD approach is based on a feed-forward convolutional network that produces a fixed-size collection of bounding boxes and scores for the presence of object class instances in those boxes, followed by a non-maximum suppression step to produce the final detections. The early network layers are based on a standard architecture used for high-quality image classification (with their last classification layer removed), which is called as the base network. In Figure 13, the base network is VGG-16, but this can be substituted with any feature extractor such as InceptionV2 or ResNet.

The SSD architecture builds on these base networks, by discarding the fully connected layers and replacing them with a set of auxiliary convolutional layers (conv6 onwards in Figure 14). These additional conv layers enable the algorithm to extract features at multiple scales and progressively decrease the size of the input to each subsequent layer.

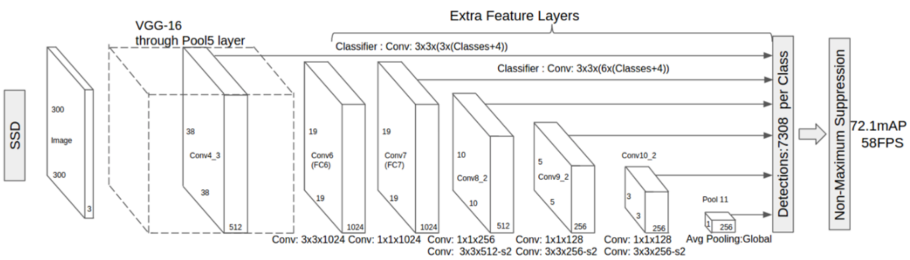


Fig. 14. SSD architecture [6] as shown above discards the fully connected layers for set of auxiliary convolutional layers enabling extraction of features at multiple scales and progressively decrease the size of the input to each subsequent layer.

The term *MultiBox* refers to a bounding regression technique based on Szedgedy's work. In SSD, every feature map cell is associated with a set of default bounding boxes of different dimensions and aspect ratios. To start with, SSD only needs an input image and ground truth boxes for each object during training. It does the following:

a. Passes the image through a series of convolutional layers, yielding several sets of feature maps at different scales.
b. For each location in each of these feature maps, it uses a 3x3 convolutional filter to evaluate a small set of default bounding boxes. These default bounding boxes are essentially equivalent to Faster R-CNN's anchor boxes.
c. For each box, it simultaneously predicts the bounding box offset and the class probability.

d. During training, it matches the ground truth box with these predicted boxes based on Intersection over Union (IoU). The best-predicted box will be labeled a positive, along with all the other boxes that have an IoU with the truth > 0.5.

Since SSD does not have a region proposal network, which would have ensured that everything we tried to classify had some minimum probability of being an "object", instead we end up with a greater number of bounding boxes with many of them having negative examples. To fix this imbalance, SSD does two things. First, it uses non-maximum suppression (NMS) to group together highly-overlapping boxes into a single box. For instance, in Figure 15, if four boxes contain the same dog, NMS would keep the one with the highest confidence and discard the rest. Secondly, the model uses a technique called *hard negative mining* to balance classes during training. In this technique, only a subset of the negative examples with the highest training loss are used at each iteration of training. SSD keeps a 3:1 ratio of negatives to positives.

The varying-size feature maps which are generated due to the extra feature layers help SSD tackle the scale problem. In smaller feature maps (e.g., 4x4), each cell covers a larger region of the image, enabling them to detect larger objects. Region proposal and classification are performed simultaneously: given p object classes, each bounding box is associated with a (4+p)-dimensional vector that outputs 4 box offset coordinates and p class probabilities. In the last step, softmax is again used to classify the object.

4 Experimental Setup

The experimental setup consists of two phases. In phase one, the algorithms were compared based on mAP and inference time for four driving conditions and four image sizes. In phase two, the best performing model of phase one was taken, and Transfer Learning was applied, as depicted in Figure 16.

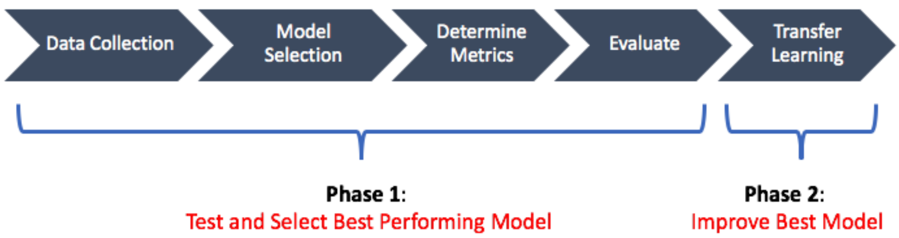


Fig. 16. In phase 1 of the experiment, the models are tested, and the best performing model is chosen. In phase 2, transfer learning was applied to improve the model's performance.

The following sub-sections explain in detail each of the aforementioned steps.

4.1 Data Collection

Most object detection models use Convolutional Neural Network (CNN) methods to train images and detect objects by identifying a region of interest within that image and determine the class of the object present within that region. Testing the pre-trained object detection models requires test images that contain reasonable clarity and visibility of the classes being identified – which the probability of detection depends.

4.1.1 Data sources. Various data sources were examined, including Google, and large University of California at Berkeley Deep Drive data sets [7]. We acquired sample data sets from Berkeley's video database and extracted images from videos we recorded while at traffic stops and parking lots at our neighborhoods. Samples taken covered different driving conditions: daytime, rainy, snowy and night.

4.1.2 Annotations using labelImg. To measure the performance of the object detection algorithms, a reference to the location of objects in the images is needed. COCO annotation format was followed to label target object classes using bounding boxes. These reference bounding boxes indicating the true location of objects in the images are referred to as GroundTruth. Comparing this GroundTruth bounding boxes to the predicted bounding boxes that are generated by the algorithms is what gives us the accuracy of the Object detection algorithm summarized by the mAP score.

A Windows Operating System open source software, LabelImg [11] was used to annotate the images. The tool allows the use of text file with predefined classes which made it easy to maintain the same class IDs as those in COCO dataset.

Approximately 100 images for the four target driving conditions were manually labeled. Figure 17 below shows the number of image instances for the different driving conditions.

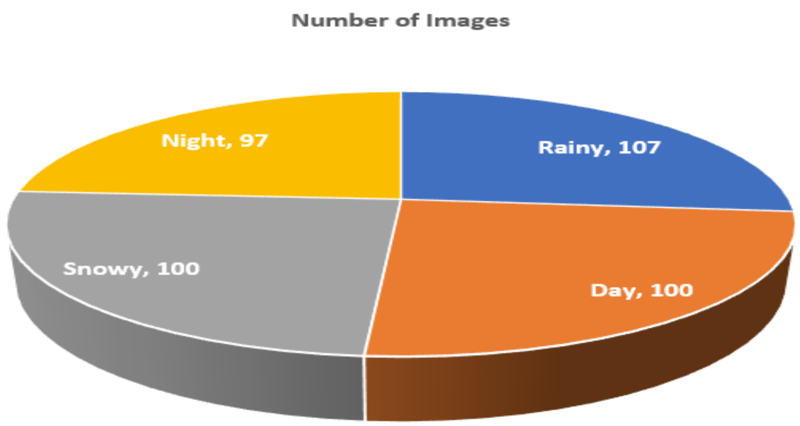


Fig. 17. Distribution of data. Above pic chart shows an approximately equal number of images used for the different driving conditions.

4.2 Model Selection

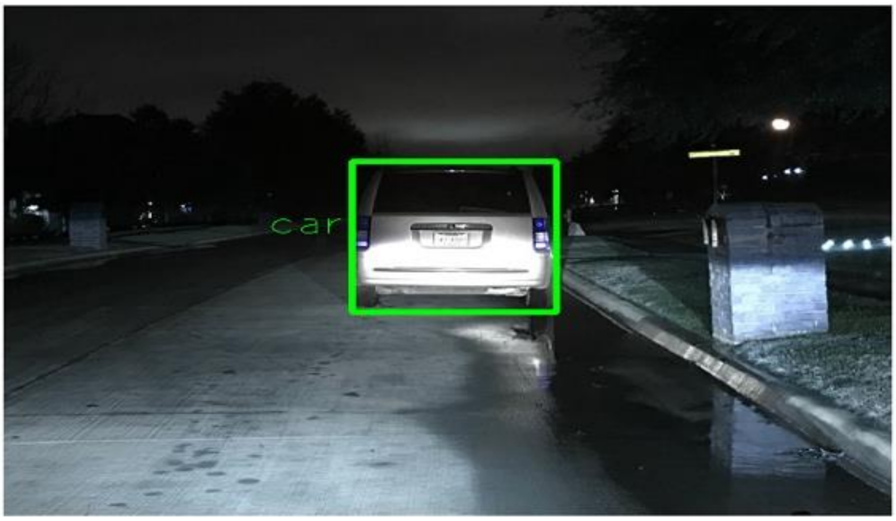
TensorFlow's object detection model zoo [8] provides several models that are pre-trained on the COCO dataset and made available for out-of-the-box inference. Since all these models were trained on the COCO dataset, they can be used for detecting the objects that are available in the COCO dataset such as humans and cars.

Three models: *faster_rcnn_inception_v2_coco, ssd_inception_v2_coco,* and *rfcn_resnet101_coco,* were chosen from the model zoo, that represent the three meta-architectures that are being compared in this research. The model names identify the meta-architecture, the feature extractor, and the training data used. For instance, the faster_rcnn_inception_v2_coco model uses faster R-CNN as the meta-architecture, inceptionv2 as its feature extractor that has been trained on COCO dataset.

In addition to providing out-of-the-box inference, TensorFlow's object detection API also makes it possible to apply transfer learning to these models using a customizable config file to either extend or fine-tune these models.

4.3 Determine Metrics

The algorithms were evaluated on how well they performed classification, predicted if an object exists in the image and localization, which is their precision of locating an object in the image. These two evaluation measures are evaluated by comparing the object detection algorithm's predictions to the ground truth data. Ground truth data provides the true labels of objects in an image. The data includes the image, classes of the objects in it and true bounding boxes for each object in the image. Figure 18 below shows a sample Ground-Truth file.



filename	width	height	class	xmin	ymin	xmax	ymax	id	xmin_scaled	ymin_scaled	xmax_scaled	ymax_scaled
IMG_5934.jpg	600	450	car	235	137	373	270	3	0.391667	0.304444	0.621667	0.6

Object location

Fig. 18. Sample ground-truth info for the location of a car in an image.

4.3.1 Localization and Intersection over Union (IOU). To evaluate the model on the task of object localization, we must first determine how well the model predicted the location of the object. Intersection over Union is an evaluation metric used to measure the accuracy of a localization task. IoU is a ratio of the area of overlap between the predicted bounding box and the ground-truth bounding box divided by the area of the union, or more simply, the area encompassed by both the predicted bounding box and the ground-truth bounding box. Refer to Figure 19 below for a visual representation of the IoU calculation, and a sample predict vs. ground truth bounding boxes.

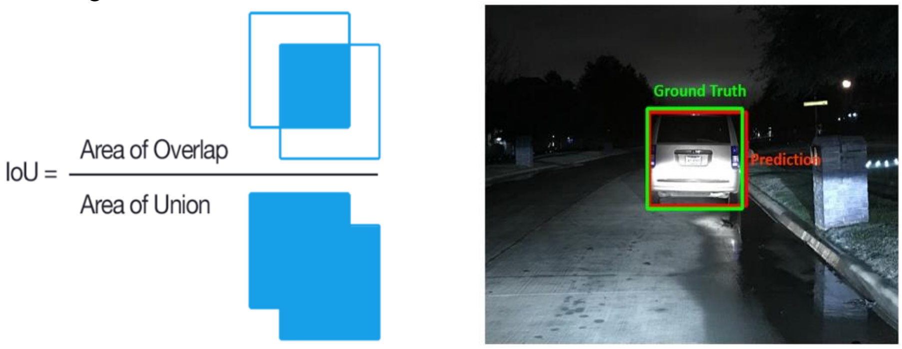


Fig. 19. Computing the intersection over union and sample image showing predicted vs ground-truth bounding boxes overlaid.

Due to varying parameters of image detection models (sliding window size, feature extractors, etc.), it is simply unrealistic to expect a total match between predicted and ground-truth bounding boxes. For this reason, an evaluation metrics that rewards predicted bounding boxes for heavily overlapping with the ground-truth is defined. Below are sample IOUs and their respective scores. For our evaluation with use IoU threshold >= 0.5 (50%). This "match" is considered a true positive if that ground-truth object has not been already used (to avoid multiple detections of the same object).

Fig. 20. Poor, Good and excellent IoU samples.

4.3.2 Mean Accuracy Precision (mAP). Mean Average Precision is the mean of average precisions (AP) for all classes detected in a dataset. To understand AP, we first must define precision and recall of a classifier. In the context of object detection algorithms, precision measures the "false positive rate" or the ratio of true object detections to the total number of objects that the classifier predicted. If you have a high precision rate, there is a high likelihood that whatever the classifier predicts as a positive detection is, in fact, a correct prediction. On the other hand, recall measures the "false negative rate" or the ratio of true object detections to the total number of objects in the data set. A high recall score means the model will positively detect all objects that are in the dataset. It is worth noting that, these two metrics are inversely related, and they are dependent on the model's performance and the threshold set for the model score. Figure 21 below shows formulas for calculating precision and recall.

$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

true positive ***(tp)*** **:** equivalent with hit
true negative ***(tn)*** **:** equivalent with correct rejection
false positive ***(fp)*** **:** equivalent with false alarm, Type I error
false negative ***(fn)*** **:** equivalent with miss, Type II error

Fig. 21. Precision and Recall formulas

In the calculation of the AP, for a specific class for example car, the precision-recall curve is computed from the model's detection output, by varying the model score threshold that determines what is counted as a model-predicted positive detection of the class. Finally, AP is computed as the area under this curve (shown in light blue) by numerical integration (Figure 22).

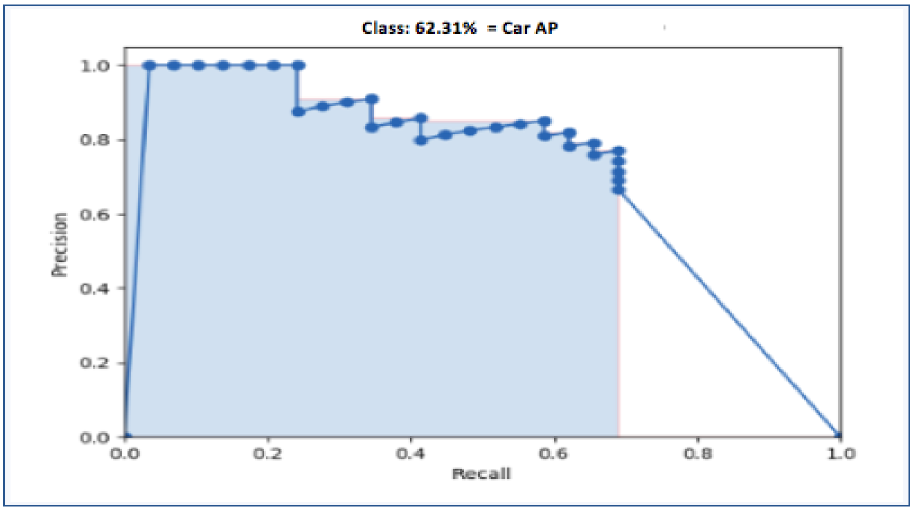


Fig. 22. Average Precision (AP) for class car is computed as the area under the curve.

Once AP for all classes is calculated, as shown above, mAP is calculated as the mean of all the AP's, resulting in a mAP value from 0 to 100%. Figure 23 below shows steps in the calculation of mAP score of 58.51% calculated by averaging the AP scores for six classes detected by an object detection algorithm.

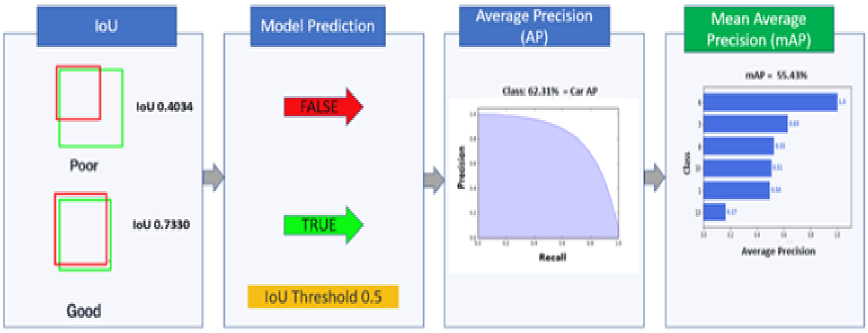


Fig. 23. Steps in calculation of mAP score begins with IoU Calculation followed by calculation AP based on a precision recall curve.

4.3.3 Inference time. This is the measure of how fast an object detection algorithm takes to infer objects detected in an image. We note the speed of detection if affected by several factors such as; Model architecture, feature extractor used, and more importantly hardware used for running the evaluations.

4.4 Evaluate

In this step of the experiment, the three models described earlier in section 4.2, were evaluated based on mAP and inference time. As the goal of phase one was to determine the best performing model, all the available images were utilized, that is, a total of 1600 images - 400 images from four driving conditions times four image widths: 150, 300, 450, 600. Comparing these algorithms on different image widths, in addition to different driving conditions, gives a comprehensive picture of how each of these algorithms performs in real-world scenarios. The result of this step is to pick the best algorithm that strikes a balance between speed and accuracy.

4.5 Transfer Learning

As the pre-trained models were trained on COCO dataset – which consists of objects that are commonly found on the road, like vehicles, stop signs, and traffic lights, and since the training data also contain similar objects, the category of Transfer Learning that is most suitable is End-of-ConvNet. Using TensorFlow's Object Detection API, the best performing model of stage 1 was re-trained by replacing the output layer with the number of categories in the training data. Additionally, several hyperparameters like batch size and number of epochs were tuned using the pipeline config file – which is a text file with several tunable hyperparameters. The end result of this step is that a new model is created, that can be used to make inferences.

5 Environment

5.1 Hardware environment

When working with large amounts of data and complex network architectures, GPUs can significantly speed the processing time. These models were evaluated and trained on Ubuntu 16.04 with GPU: GeForce GTX 1060 with 16GB memory. TensorFlow with CUDA toolkit 9.2 and cuDNNv7.0 was used to train the models during Transfer Learning phase.

5.2 Tools

Google released pre-trained models with various algorithms trained on the COCO dataset for public use [8]. The API is built on top of TensorFlow and intended for constructing, training, and deploying object detection models. The APIs support both object detection and localization tasks. The availability of pre-trained models enables the fine-tuning of new data and hence making the training faster.

6 Results

In phase one of our experiment, the algorithms are evaluated to determine which works best under different driving conditions. In phase two, Transfer Learning is applied to the model selected from phase one. The results are discussed in two phases.

6.1 Phase 1: Determine the best model

6.1.1 Heat Map of mAP scores across algorithms and driving conditions: As discussed in the evaluation section 4.3.2 above, mean Average Precision (mAP) is the primary evaluation metric used, and it is the average of the maximum precisions at different recall values. mAP gives a one number summary measuring the accuracy of localization and classification for a given object detection algorithm. In Figure 24 below, the mAP heatmap for varying image width on different driving conditions for the three Meta-Architecture is shown. Considering that the pre-trained models were trained on COCO dataset image size, 600 X 600 as indicated on the TensorFlow Model Zoo directory [8], varying the image width is impacts the mAP score achieved by a given algorithm. mAP score increases as the image width increases from 150 to 600. Region-based architecture i.e., R-FCN and Faster R-CNN outperformed the SSD. For the limited dataset used, all the algorithms have higher mAP scores for the snowy condition compared to the rest of the conditions.

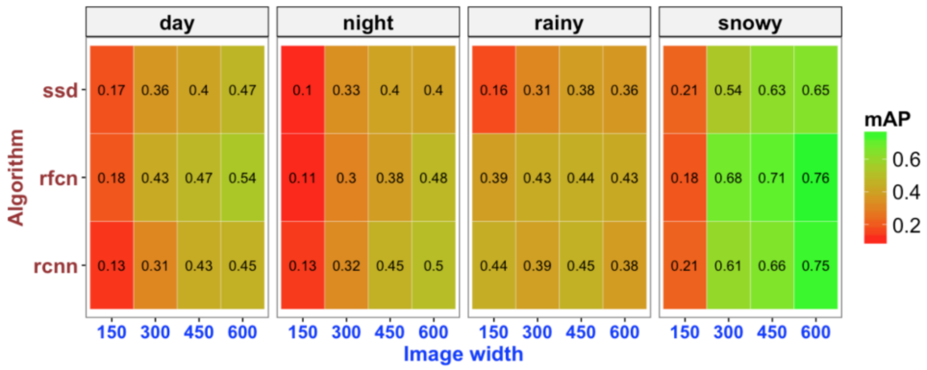


Fig. 24. Heatmap of mAP scores shows that these algorithms performed well under snowy conditions with rfcn and faster-rcnn having higher mAP scores than ssd for all conditions.

6.1.2 Inference time comparison of algorithms across different driving conditions: Looking at the speed of detection, SSD leads the pack, closely followed by faster R-CNN. Even though R-FCN did well from a mAP perspective, it lagged behind in terms of detection speed as shown in the heatmap in Figure 25 below.

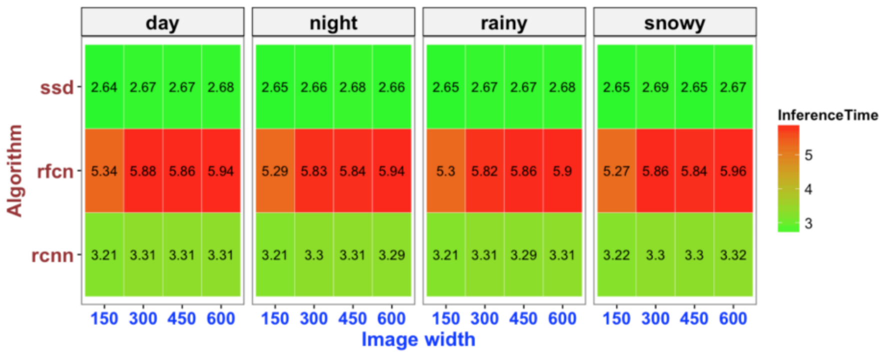


Fig. 25. Heatmap of inference times in seconds shows that ssd has better inference times over both the region-based algorithms.

6.1.3 Density plot showing distribution of inference time across different driving conditions and image sizes: Looking at inference time distribution in Figure 26 below, image size and driving condition do not impact speed of detection for both SSD and Faster R-CNN. On the other hand, there is a slight positive correlation between image size and inference time for R-FCN where the inference time increases with the increase in image size.

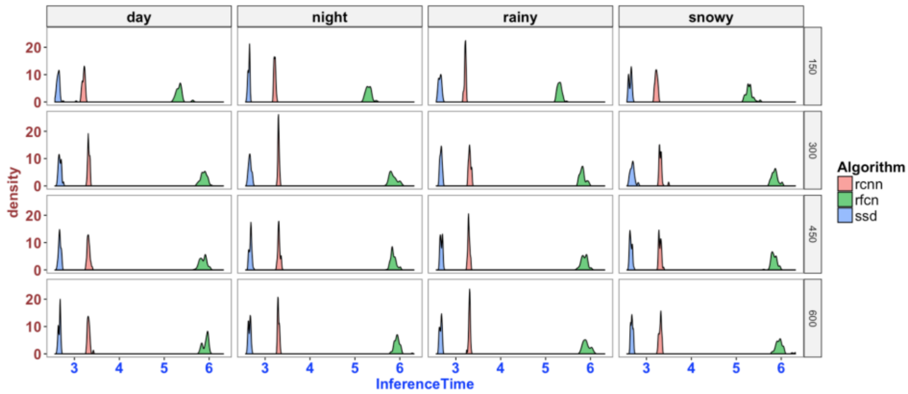


Fig. 26. Density plot of inference times reveals that ssd and r-cnn are pretty close and rfcn is the slower for all image sizes and conditions.

6.2 Phase 2: Use Transfer Learning

The results from phase 1 clearly indicate that region-based algorithms have higher mAP scores than SSD. Of these, R-FCN has the best mAP scores in three of the four conditions (Figure 24) but has the worst inference times as indicated in Figure 25. Upon close observation of phase 1 results, faster R-CNN is not very far behind from R-FCN in terms of mAP score and has almost equal inference times as SSD as indicated in the density plot Figure 26. These observations prompted the selection of faster R-CNN for phase 2 evaluation. The results of applying Transfer Learning are compared with baseline faster R-CNN, which are discussed next.

6.2.1 Comparison of mAP score between baseline vs transfer learning model. After applying transfer learning to faster R-CNN baseline model, a new model a rcnn-custom is created. A comparison of mAP scores of these two models is shown in Figure 27. From this figure, mAP scores are shown to have improved for night and rainy conditions.

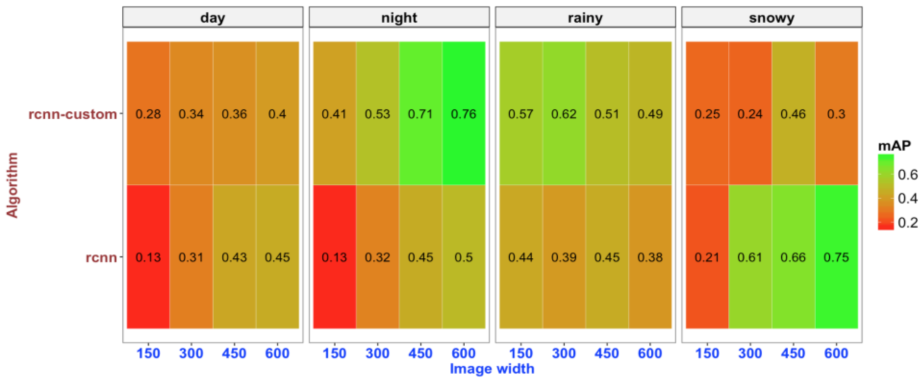


Fig. 27. mAP score of baseline vs transfer learning model shows that the custom model performed better in night and rainy conditions.

6.2.2 Comparison of inference time between baseline and transfer learning model: A side-by-side box plot of inference times of faster rcnn custom and baseline model (Figure 28) clearly indicates that the inference times have reduced after applying Transfer Learning.

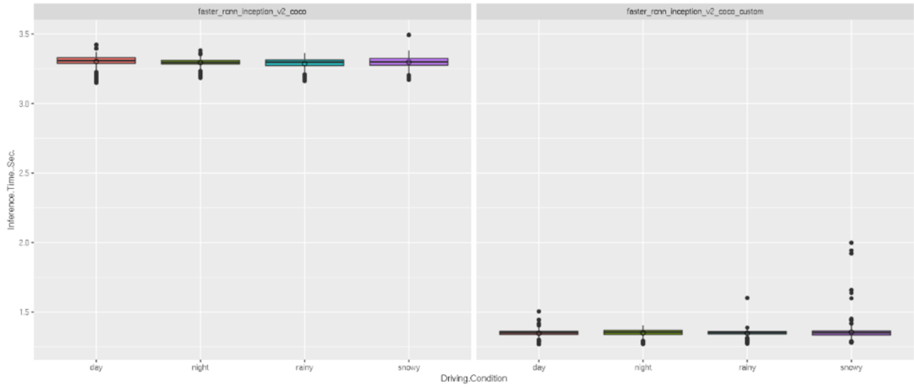


Fig. 28. Inference time of baseline vs Transfer Learning model shows that the custom models inference times are better for all conditions.

6.2.3 Comparison of inference time between baseline and transfer learning model: To show the effectiveness of Transfer Learning, we show a comparison of our custom model with the rest of the models in Figure 29. It can be readily observed that our model outperformed all the pre-trained models.

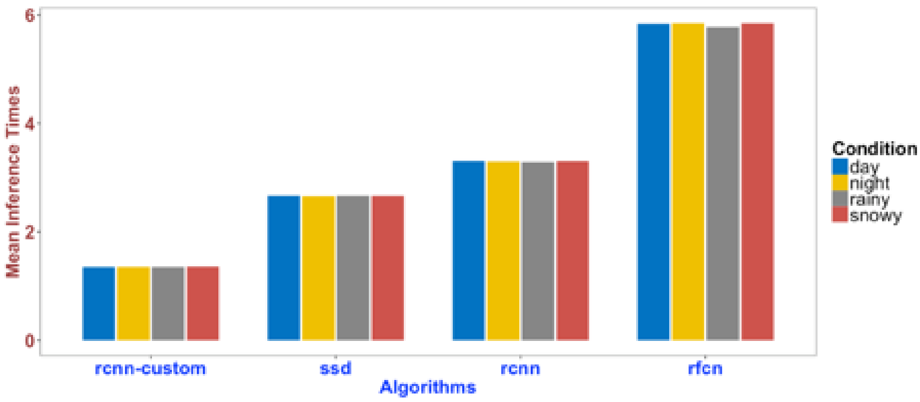


Fig. 29. Comparison of inference times shows that rcnn-custom model outperforms all the other models for all the driving conditions.

7 Related Works

An empirical evaluation of deep learning algorithms on highway driving conditions was conducted by Huval et.al. [9]. In this work, the research team used regular CNNs for vehicle and lane detection on highways. By using Camera, Lidar, Radar, and GPS they built a highway dataset consisting of 17 thousand image frames with vehicle bounding boxes and over 616 thousand image frames with lane annotations. Using this dataset, they trained a CNN and showed that regular CNNs are capable of detecting vehicles and cars in a single forward pass. Their results show that CNN algorithms are capable of good performance in highway lane and vehicle detection, however their work omitted temporal information which is an important component in lane and vehicle detection systems.

Many object detection algorithms have been developed in the recent years which are based on Convolutional Neural Networks. While each algorithm has individually presented its speed and accuracy metrics, what is lacking is a comprehensive comparison of these algorithms. Dai et al, presented a region-based fully convolutional network (R-FCN) for object detection and reported that they achieved an accuracy close to Faster R-CNN but with better training time [10]. Liu et al. introduced SSD [6], a single-shot detector for multiple categories that is faster than the previous state-of-the-art for single shot detectors (YOLO), and significantly more accurate, in fact, as accurate as slower techniques that perform explicit region proposals and pooling (including Faster R-CNN). Finding a way to do an apples-to-apples comparison of these algorithms is the biggest challenge. For instance, some algorithms use different base feature extractors like VGG or Residual Networks, while some others work well with certain image resolutions and yet some others have been specifically trained on certain hardware and software platforms. Huang, et al. attempted to address this problem by using a unified implementation of Faster R-CNN, R-FCN and SSD systems, which they call as "meta-architectures" [12].

The idea behind using a unified approach is that it is impractical to compare every recently proposed detection system. By grouping algorithms based on common set of architectures, it is possible to compare many algorithms that share similar characteristics. In particular, the group of researchers have created implementations of the Faster R-CNN, R-FCN and SSD meta-architectures, which at a high level consist of a single convolutional network, trained with a mixed regression and classification objective, and use sliding window style predictions. The results show that using fewer proposals for Faster R-CNN can speed it up significantly without a big loss in accuracy, making it competitive with its faster cousins, SSD and R-FCN. They also showed that SSDs performance is less sensitive to the quality of the feature extractor than Faster R-CNN and R-FCN.

The speed and accuracy trade-off– the gains in accuracy are only possible by sacrificing speed and vice-versa, is a ubiquitous problem in self-driving cars. The decision to choose one architecture over other boils down to finding the sweet spot between accuracy/speed trade-off curve. An empirical evaluation of the performance of these architectures/algorithms for solving object detection problems in the context of self-driving cars under varying driving conditions has not been attempted.

8 Ethics

We have acquired our test data from Berkley object detection data repository [7] and videos recorded around our neighborhoods. We have used a python script to extract some of images used for research.

We believe we have acted responsibly and professionally while handling the test data in our hand, with the intension of evaluating and improving existing object detection algorithms in the context of Self Driving cars, expected to support the public good. In that way, we completely adhere to "The ACM Code of Ethics and Professional Conduct [13] guidelines.

We adhere to *General Ethical Principle*s as our work would definitely fit into one of a kind research specific to evaluating top quality object detection models potentially used in the race of finding best solutions for object detection technology in the inevitable Self Driving Car future. Our research is honest and trustworthy, did not pose harm to any stakeholder as this is not implemented or not in the process of capturing data, expected to contribute to society and to human well-being if this research can be used for further studies. The research required adaption from lot of great work already done in this area, and leveraged already existing tools, code, journals as cited in the paper to respect others work, innovations and creativity. The test data collected and used for testing is not expected to be published on social sites or used for any commercial purposes to respect the privacy and honor confidentiality of the subjects in the images.

We strongly acted upon our *Professional Responsibilities* to strive to achieve high quality in both the processes and products of professional work. We have leveraged existing object detection models available from COCO object model zoo [8], open source tools such as LabelImg [11] for creating ground truth labels and annotation.

We take pride having demonstrated our *Professional Leadership Principles* by developing an idea that can further create more opportunities for members of the Data Scientist community and professional working on similar projects in near future. A fail-proof all-weather solution is extremely needed for the success of Self Driving Car to operate safely and socially acceptance environment.

Finally, the project is completely technical in nature and applied various deep learning techniques. The progress should not have been possible without amazing and extensive work done by many researchers that we leveraged as explained in the earlier sections. By citing the references in our paper, we uphold, promote and respect the principles of *Compliance with the Code*.

9 Conclusion

Based on the study, we conclude that no single algorithm works best for all conditions. However, retraining and optimizing with domain-specific data using Transfer Learning is likely to improve performance in similar conditions.

In this research, we have evaluated the performance of 3 object detection architectures based on the 2 metrics - mAP score and inference time. Our results show that region-based algorithms such as Faster R-CNN and R-FCN tend to have a high accuracy and SSD based algorithms have faster inference times. As our dataset comprised of images taken under four different driving conditions, we were able to evaluate the performance of each of these algorithms under different driving conditions. Our results show that these algorithms tend to perform well under snowy conditions. We also proved that we can take a generic pre-trained model and apply transfer learning to improve the inference times by about three seconds per image. Transfer learning also proved to be effective in improving the mAP scores even with a small training dataset of 240 images (60 images per condition) for three of the four conditions.

10 Future Work

The research enables much more opportunities to improve further. The number of test images can be increased substantially and tested with streaming videos to perform more practical real-world applications of self-driving cars and other autonomous vehicles or devices. The research can be performed with models from object detection model zoo and with newer approaches to test similar comparisons under varying weather conditions. The research can be extended to test the models in real-time self-driving car implementation by integrating with sensor data. The performance of mAP scores and inference time can be improved by tuning other hyper-parameters and additional layers in the Transfer Learning step – using high-performance GPU systems.

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Appendix:

Project Code Location

The Project code is stored in public GitHub repository, which contain code, data and documents supporting the research work available at https://github.com/kevin-okiah/CAPSTONE for reference and further enhancements.