addition, following the multitasking loss for Fast R-CNN, the objective function has been reduced to a minimum. This loss function is shown in the following equation (2) , the details of the Equation also can be seen in [10].

$$L(\{p_i\},\{t_i\})\frac{1}{N_{cls}}\sum_i L_{cls(P_i,P_i^*)+\lambda\frac{1}{N_{reg}}\sum_i p_i L_{reg(t_i,t_i^*)}} \quad (2)$$

2.2.2 Sharing Features for RPN and Faster R-CNN

Until now, it has been explained how to train a network to generate a region proposal without taking into account the region-based object detection. Here, Faster R-CNN is used for the detection network. After that, a unified network learning algorithm consisting of shared convolution layer RPN and Faster R-CNN is defined.

Here both RPN and Faster R-CNN are trained independently and the layers of convolution are characterized by different forms. For this reason, instead of learning two separate networks, techniques have been developed that are able to share layers of convolution between two networks. There are three techniques to train networks in shared properties. These are alternating training which are, approximate joint and non-approximate joint trainings respectively.

2.3 Comparison of Faster R-CNN and R-CNN Methods

Today, the most sophisticated object detection networks are based on region proposal algorithms for the description and identification of object locations.Faster R-CNN has put forward the regional proposal calculation as a bottleneck by reducing the working time of these detection networks in R-CNN. In the Faster R-CNN, a Region Proposition Network (RPN) is implemented that shares full image convolution characteristics using the detection network, so that almost free region proposals can be made. Faster R-CNN, along with the improved RPN, do not require external zone recommendations, unlike R-CNN. In addition, the RPN improves the quality of the district proposal and thus improves the overall accuracy and speed of object detection.

3 Detail's of Implementation

This study aims to successfully train the vehicle detector on the sample vehicle data sets using the Faster R-CNN and R-CNN deep learning methods, shown in Section. It also aims to achieve maximal results for vehicle detection by testing the trained vehicle detector on the test data. In addition, the results obtained from these methods are compared with experimental analysis. To do this, the Caffe deep learning framework is used on the Matlab Program.

The purpose of this study is to successfully train our vehicle detector using R-CNN, Faster R-CNN deep learning methods on a sample vehicle data sets and to optimize the success rate of the trained detector by providing efficient results for vehicle detection by testing the trained vehicle detector on the test data. The working method consists of six main stages. These are respectively; loading the data set, the design of the convolutional neural network, configuration of training options, training of the Faster R-CNN object detector, evaluation of trained detector. In addition, in the scope of the study, Faster R-CNN, R-CNN deep learning methods were mentioned and experimental analysis comparisons were made with the results obtained from vehicle detection.

Our application consists of 6 main steps. These; loading the data set, the design of the convolutional neural network, configuration of training options, training of the Faster R-CNN object detector, evaluation of trained detector.

First, the loading of the data set is performed. In this study, two different vehicle dataset were employed. The first dataset includes approximately 350 images [11] and 1000 images are obtained from the second public vehicle dataset [12] . Each image in these datasets includes one or two tagged vehicle samples . In this study, the training data is stored on a table. The existing columns on the table contain the contents of the path of the image files and the ROI tags for the vehicles. In addition, in this section, the data set is divided into training and test sets to train the detector and evaluate the detector. In this part, in order to train the detector, 60% of the data is selected as the training set, and the remaining data is selected and used as the test set for