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# Deep learning-based vehicle occupancy detection in an open parking lot using thermal camera

Vijay Paidi<sup>1</sup>, Hasan Fleyeh<sup>1</sup>, Roger G. Nyberg<sup>1</sup>

<sup>1</sup>Dalarna University, School of Technology and Business studies, Borlänge, Sweden

**Abstract:** Parking vehicle is a daunting task and a common problem in many cities around the globe. The search for parking space leads to congestion, frustration and increased air pollution. Information of a vacant parking space would facilitate to reduce congestion and subsequent air pollution. Therefore, aim of the paper is to acquire vehicle occupancy in an open parking lot using deep learning. Thermal camera was used to collect the data during varying environmental conditions such as; sunny, dusk, dawn, dark and snowy conditions. Vehicle detection with deep learning was implemented where image classification and object localization were performed for multi object detection. The dataset consists of 527 images which were manually labelled as there were no pre-labelled thermal images available. Multiple deep learning networks such as Yolo, ReNet18, ResNet50 and GoogleNet with varying layers and architectures were evaluated on vehicle detection. Yolo, GoogleNet and ResNet18 are computationally efficient detectors which took less processing time while Resnet50 produced better detection results compared to other detectors. However, ResNet18 also produced minimal miss rates and is suitable for real time vehicle detection. The detected results were compared with a template of parking spaces and IoU value is used to identify vehicle occupancy information.

## 1. Introduction

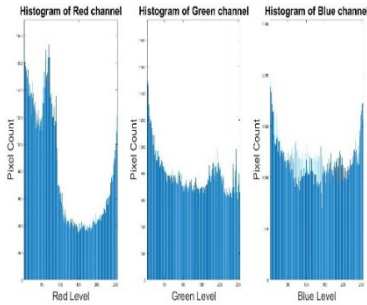
Parking can be a daunting task due to availability of limited number of parking spaces compared to the number of vehicles. According to previous studies, it can take up to 14 minutes to find a parking space [1, 2]. It can lead to congestion, increased air pollution and user frustration. Therefore, parking management is an integral component for city planning administrators and this is one of the research themes in a smart city development. Innovative parking has been an important research area as it enables accessibility to commuters and is capable of enhancing business opportunities [3]. Parking problem is applicable to both major and minor cities due to higher demand and limited resources, though there can be a difference in demand between different places. Lack of parking spaces at places of interest can lead to loss of business opportunities. Therefore, business organizations spend higher expenditure to acquire sufficient number of parking spaces which cover large areas of scarce land resources. Due to space restrictions, in urban areas, new parking areas are being built in multi storey buildings or basements. In order to avoid parking problems, public transport can be utilized. However, using public transport all the time might not be a convenient option for everyone. The other way is to use smart parking applications to efficiently utilize parking spaces and reduce congestion, user frustration and pollution.

There are several web and mobile smart parking applications available. Smart parking applications are available for closed parking lots while there are no applications available for open parking lots [3]. Demand of parking spaces in an open parking lot is higher compared to a closed parking lot. An open parking lot is subjected to different environment conditions such as; snow, rain, darkness and sunny. The expenditure made on a parking guidance system or smart parking application for open parking lots cannot be retained directly as the parking spaces

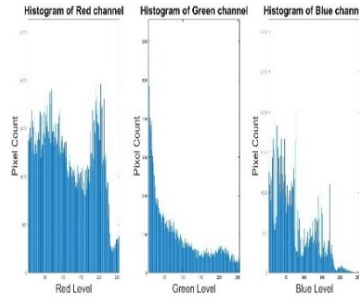
are available freely. There are several tools used to identify parking occupancy such as; infrared and ultrasonic sensors, magnetometers, vehicle ad hoc networks (VANET) and microwave radars [4, 5]. However, sensors, VANET, microwave radars and magnetometers need higher expenditure in installation and maintenance activities. Therefore, computer vision is a suitable technology to identify parking occupancy which is capable of covering large number of parking spaces with a single camera. The number of parking spaces covered by a camera is dependent on the focal length, height and angle of the positioned camera. Since computer vision is one of the feasible smart parking tools for open parking lots, a thermal camera is used to capture data in this paper. A thermal camera is expensive compared to a digital colour camera, but it facilitates in detecting objects in any weather and light conditions and it also has less privacy restrictions. Object detection was implemented to identify vehicles which comprises of image classification and object localization phases. A multi-object detection was performed since the parking lot consists of multiple vehicles. Emphasis was given to deep learning architectures as it is one of the intelligent contemporary methodologies which do not need custom modifications or morphological operations to detect and classify an object. Since there are already well-defined deep learning architectures, some of them were implemented and evaluated on thermal data in this paper.

There are several smart parking solutions available as mentioned earlier. However, there is no smart parking tool which is suitable for all economic, geographic and environmental conditions. Therefore, a large-scale utilization of smart parking solutions is still not available. The current available smart parking applications are limited to few parking lots in several countries and none of these applications provide parking occupancy information for an open parking lot. Therefore, this paper aims to identify vehicle occupancy information in an open parking lot with

(1.1) Sunny in winter morning



(1.2) Dark snowy winter morning



(1.3) Dusk or dawn

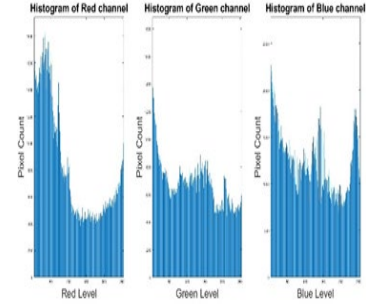


Figure 1. Diverse images in the dataset with histogram

deep learning and thermal camera. The first step is to identify vehicles using object detection algorithms. The second step is to compare the vehicle detection results with a template of parking spaces and acquire vehicle occupancy information.

A thermal camera is commonly used for security applications or to identify overheated equipment [6]. The use of a thermal camera for identifying parking occupancy was not discussed in previous literature. However, when it comes to digital colour camera, there are several studies available in the literature. Therefore, the contribution of the paper is two folds. In the first fold, the paper addresses this research gap by using a thermal camera to capture data of an open parking lot. While in the second fold, deep learning object detection algorithms such as Yolo, ResNet18, ResNet50 and GoogLeNet architectures were implemented to identify vehicles and their performance is evaluated. These algorithms work efficiently in previous literature using images or videos provided by colour camera. However, the performance of these detectors was scarcely evaluated using a thermal camera.

The remaining sections of the paper is organized in the following way. Section 2 discusses relevant literature while Section 3 discusses about the dataset and set of detectors used in this paper. Section 4 presents the results obtained in this paper along with analysis. Section 5 discusses efficiency of detectors, pros and cons of using a thermal camera for parking occupancy detection. Finally, the paper is ended with conclusion in Section 6.

## 2. Literature review

Extensive research on the use of various algorithms or detectors for identifying vehicles or other objects is already available. Object detection capability kept evolving over the years and new detectors or architectures were generated. Since, vehicle occupancy detection was performed using a camera, relevant algorithms or detectors are discussed in this section. Edge detectors such as Canny and Sobel can be used to identify vehicles [7] [8]. Edge

detectors perform efficiently when the vehicles can be recognized. However, when using thermal cameras, due to loss of heat in the vehicle over a period of time, they can become dark and can be challenging to recognize or detect using edges. In such scenarios edge detectors might not be a suitable option for vehicle detection. Histograms of Oriented Gradient (HOG) descriptors and Viola Jones are efficient human or pedestrian detectors [9] which can also be used for vehicle detection. HOG detector trains using positive and negative images using a linear Support Vector Machine (SVM) classifier [10].

In another study, Kalman filter was used to identify and classify night time traffic surveillance [6]. Headlight and visible vehicle features were used to detect vehicles. Similarly in another study, [11] vehicles during night time were detected using blob properties which were classified by an SVM classifier and Kalman filters were invoked to track the detected vehicles. In another study, infrared thermal camera was used to study traffic flow using Viola Jones detector. The tires and windshield of the vehicles were used to identify the vehicles [12]. Based on the chosen features, positive and negative images were used to train the detector. However, since the vehicles are moving on the road, heat can be captured by the windshield or by the tires which might not be applicable to this paper, since the vehicles are stationary in a parking lot. In a similar study, an unmanned aerial vehicle with help of a thermal camera is deployed for detection of people and cars [13]. Detection of people and cars was performed using multiple cascaded Haar classifiers. Haar uses a set of weak classifiers to form a strong classifier. However, the position and angle of the vehicle affects the classification [11]. Haar also requires good edges and lines for better detection which is a challenge due to varying temperatures of vehicles in an open parking lot. Increased performance normally requires higher computational costs and in order to maintain accuracy with lower computational costs a binary sliding window detector also called ACF detector was developed [14, 15]. An image is computed to multiple channels and then sum every block

of pixels to generate lower resolution channels. A multi scale sliding window is employed and boosting is performed to identify object in ACF. Multiple additional frame boxes or bounding boxes can be created where non-maximum suppression and threshold can be used to reduce the detected bounding boxes.

Neural networks are an evolving data processing system used for classification purposes. It is inspired by the human brain nervous system where extracted features are passed through layers to generate high dimensional information [16]. Deep learning is capable of handling complex object detections and is one of the popular methods available [17]. Deep residual learning framework improves detection and accuracy of a convolutional neural network [18] and were implemented in this paper. Pre-trained residual learning networks with varying layers is available which can be used to perform custom detection [19]. Similarly, there are several other frameworks with varying architectures and performances. Googlenet is one such deep learning architecture which consumes less computational costs [20]. Therefore, it is selected as one of the object detection algorithms in this paper. Faster Regional Convolutional Neural Network (FRCNN) is a deep learning neural network object detector where sliding window detector and region proposal networks were used [21]. This object detector can be combined with existing deep learning architectures to make use of well-developed architectures and improve the accuracy. Yolo is another popular model used for classifications which is fast and computationally efficient. It uses a single convolutional neural network to detect the objects of interest. Yolo model was used in to count traffic [22] and people [23] with high accuracy. Since Yolo is a computationally efficient classification algorithm, it is also used as one of the detectors in this paper.

### 3. Data and method

This section describes about the data collection, processing, implementation of algorithms and parking occupancy generation.

#### 3.1. Data with thermal camera

The data for vehicle occupancy detection was captured using an Axis Q1942-E thermal camera. The thermal camera was installed on a two-storey building and was equipped with 19mm focal length objective. The viewing angle is 32 degrees and detection range of a vehicle is 1757 meters. Only first four rows of the parking lot were selected to identify vehicle occupancy as shown in Figure 1. The green rectangular region is the region of interest. The vehicles outside region of interest are small and majorly occluded which was the reason for exclusion. The data was collected in different weather conditions such as snow, rain, dark and bright conditions. The installed thermal camera records videos based on motion detection which lead to collection of several small interval videos in various weather conditions. The videos are accessed and stored on a local disk using an application. The size of the total collected videos is nearly 30 gigabytes. Few frames from these videos was collected and stored which represents diverse conditions. Each image consists of various vehicles and the size of each image is 600x800 pixels.

In Scandinavia or other similar countries, daylight is shorter during winter and longer during summer. Snow can be seen for three to four months during winter. A digital colour camera can face issues with low light levels and snow conditions which are common in Scandinavian or other similar countries. Based on the privacy policy guidelines in Sweden, it is restricted to use video surveillance in open public areas where individuals can be recognized or identified [24]. Therefore, the use of thermal camera had facilitated to avoid these restrictions where no individuals can be identified or recognized. In this way 527 images were collected from several videos.



Figure 2. Area of parking spaces

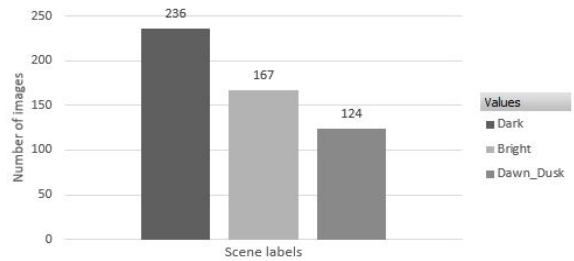


Figure 3. Count of diverse images

The test parking site used in this study is in Sweden where the vehicles arrive between 7:00 and 8:00 in the morning and leave the parking space around 16:00-17:00. There are heaters located in the parking lot which would be used before leaving. The use of heaters generate heat in the vehicles which can be seen in Figure 1.2 where one vehicle can be seen bright even in dark evening conditions. In the morning, vehicles are warm and can be easily identified during winter or sunny conditions. Figure 2 illustrates the diverse images collected from the thermal camera. Figure 1.1 illustrates the vehicles in bright conditions, Figure 1.2 illustrates vehicles in dark conditions while Figure 1.3 illustrates vehicles in dawn and dusk conditions which are subjected to shadowy regions. The histograms of the three images illustrate the variance of pixels in RGB channels during each condition. In bright conditions, RGB pixels were mostly similar. In dark conditions, Red pixels are in higher proportion while in dawn or dusk conditions, Blue and Green pixels are in higher proportion. During dark conditions, heat in the vehicles reduce over a period and they appear dark making it hard to detect as shown in Figure 1.2. The thermal camera uses pseudo colours to display data as shown in Figures 1 and 2 where bright colour represent warm objects while blue or dark colour represent cooler objects. Figure 3 illustrates the diversity of the images in the dataset collected in various light conditions. Images were

divided into three scenes; bright, dark, dawn or dusk. The bright images consist of vehicles with bright colour like Figure 1.1. The dark images consist of several greater number of red pixels leading to darker images as shown in Figure 1.2. Dawn or dusk images consists of shadows leading to a greater number of green and blue pixels as shown in Figure 1.3.

### 3.2. Labelling the dataset

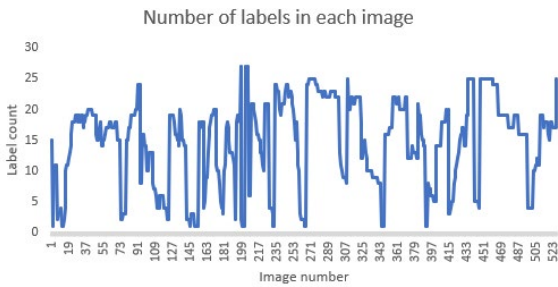


Figure 4. Dataset label count

The pre-trained vehicle detection algorithms could not identify all the vehicles in the dataset for automatic label creation. Since there were no pre-labelled dataset available, vehicles were labelled manually, and occupied spaces were labelled as cars. Diversity between the images was maintained to improve feature detection. Each image consists of 30 parking spaces and Figure 4 illustrates the number of vehicles labelled in each image. Total number of labels in the dataset were 7777. The average size of each label is 90x80 pixels. The dataset is divided so that 70% of the images were used for training and 30% for testing. The images were randomized before the division of training and test datasets where 368 images were part of training set while 159 images were part of testing.

### 3.3. The Detectors

The detectors implemented in the paper are:

- Yolo v2: It is logistic regression based multi object detection algorithm with low computation overhead. It uses a single convolutional neural network which makes it faster compared to other object detection algorithms. It divides the image into 7x7 grid and uses two bounding boxes along with predicted probabilities for object detection [23].
- GoogleNet: It is a 22-layer pre-trained deep learning network which is computationally efficient [25]. It uses several small convolutional neural networks which reduces the number of parameters leading to faster object detection. The last three layers were updated to train with thermal images dataset and Faster RCNN is used to perform object detection.
- ResNet50 and ResNet18: ResNet50 is a 50-layer pre-trained deep learning network while ResNet18

is an 18-layer deep network. Resnet uses identity shortcut connections to skip layers and avoid gradient vanishing problem with deep networks [18]. Faster RCNN is used with ResNet18 and Resnet50 layers to perform object detection.

### 3.4. Evaluation metrics

The same set of training and test images were used for all the algorithms. The detectors were evaluated using log-average miss rate curve which consists of False Positive Per Image (FPPI) with respect to miss rate. The vehicle occupancy is captured using two steps. The first step is to identify vehicles using detectors with a threshold of 0.5 and the second step is to perform Intersection over Union (IoU) with a template of parking spaces and generate parking occupancy information. The IoU measures the overlap between two bounding boxes where one bounding box is the identified vehicle while the other bounding box is the pre-defined parking space or ground truth. If the IoU is greater than 0.2, it assumes the parking space is occupied and if the IoU value is less than 0.2 it assumes it as a free parking space. With higher IoU value false positives were identified, therefore the IoU value is decreased to 0.2. This is due to overlapping bounding boxes due to occluded images of vehicles. A free parking space is represented by green rectangles and red rectangles represent occupied parking spaces. Yolo, GoogleNet, ResNet18 and Resnet50 used 10 epochs and 0.001 base learning rate for training. Pre-trained GoogleNet, ResNet18 and Resnet50 networks were used as they were experienced in extracting features from several images and provide better detection rates [26]. The training was performed using a Nvidia Quadro P5200 GPU.

## 4. Results and Discussion

This section discusses and analyses the results obtained from implementing the detectors.

### 4.1. Yolo v2

Yolo lead to better detection results as illustrated

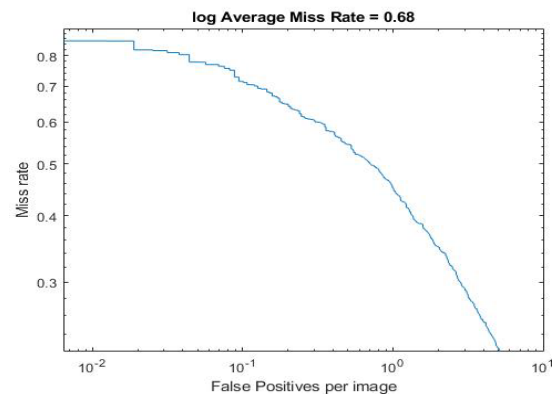


Figure 5. Yolo average miss rate



in Figure 5. Computation time is low and efficient as shown in Table 1. However, the log average miss rates of Yolo is 0.68. The FPPI are between 1 to 7. More number of training images might be necessary to reduce the miss rate and improve the detection rates. The vehicle occupancy information acquired by Yolo is illustrated in Figure 6 which acquired positive detection rate of 96%.



Figure 6. Yolo vehicle occupancy

#### 4.2. GoogleNet

GoogleNet deep learning network lead to poor detection results. FPPI and miss rates were very high leading to log average miss rate of 0.84 as illustrated in Figure 7. GoogleNet generates a smaller number of parameters to improve the computation compared to other deep learning networks. However, this might have reduced detection performance in different environmental conditions. High number of training images can facilitate to reduce the miss rate and false positives.

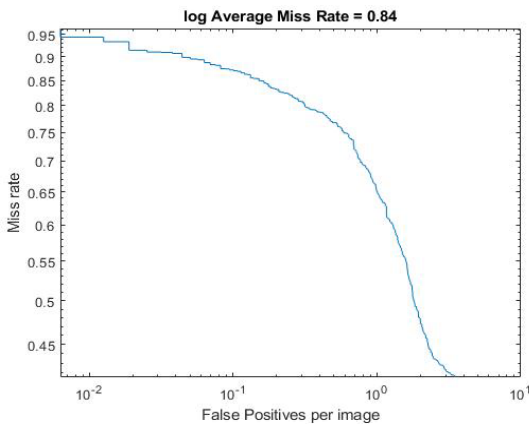


Figure 7. GoogleNet average miss rate

The vehicle occupancy information acquired using GoogleNet is illustrated in Figure 8, where positive detection rates was approximately 76%. There are false positives and false negatives detections to the right side of the image.

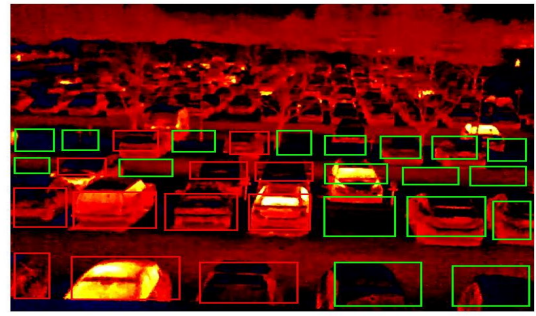


Figure 8. Vehicle occupancy using GoogleNet

#### 4.3. ResNet18

ResNet18 performed better than Yolo and GoogleNet detectors. The average log miss rate is 0.06 where FPPI and miss rates are minimal as illustrated in Figure 9.

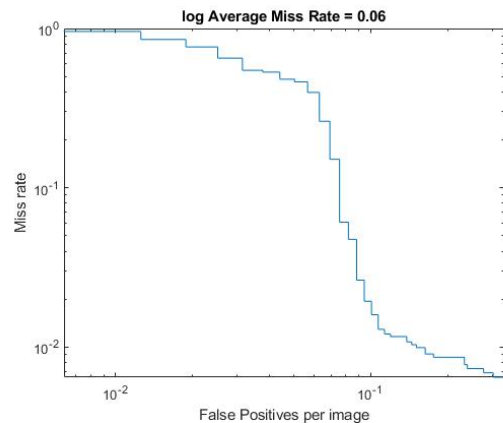


Figure 9. ResNet18 average miss rate

The use of residual learning framework facilitated in improving the detection rates. The number of layers in this network is 18 which is less than GoogleNet. However, the miss rates were significantly less when compared to GoogleNet. The computation time is also less which takes nearly 1 second to get detection results from each image. When using this network on real time videos, number of frames can be reduced to provide real time vehicle occupancy information. The vehicle occupancy information is illustrated in Figure 11 and 12 which acquired 100% detection rates.

#### 4.4. ResNet50

The ResNet50 performed better than previous detectors and the average log miss rate is 0. There were very minimal FPPI and miss rates identified as illustrated in Figure 10. The combination of pre-trained deep network and residual learning framework facilitated in improved performance of the detector. The number of layers were also high compared to other detectors. Therefore, the computational costs and processing time was also higher using this architecture. It took between 2-4 seconds to provide detection results for each image using a single GPU as shown in Table 1. The positive detection rates of ResNet50 and ResNet18 was 100% as illustrated in Figure 11 and 12.

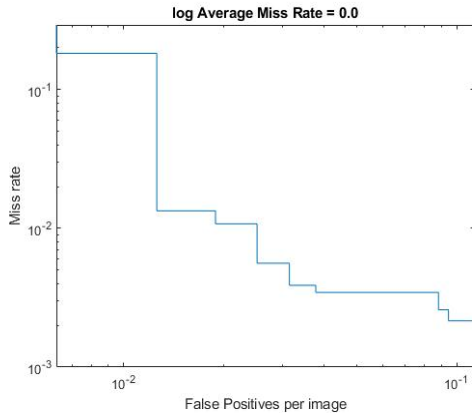


Figure 10. ResNet50 average miss rate



Figure 11. Vehicle occupancy in dusk conditions

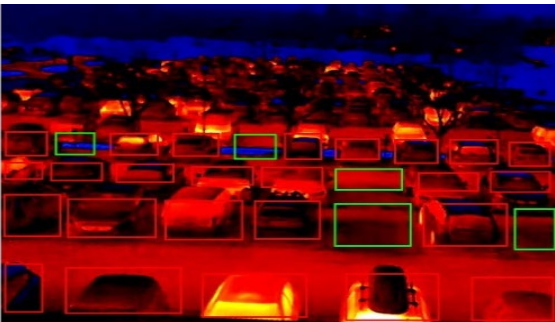


Figure 12. Vehicle occupancy in dark conditions

#### 4.5. Discussion

This paper uses thermal camera and deep learning for vehicle occupancy detection. There were no previous studies that used thermal camera for parking occupancy. Therefore, this study serves like an experiment, evaluating the performance of deep learning networks on thermal camera. The number of images in the training dataset is low for the purpose of object detection. The available pre-trained detectors are trained with thousands or millions of images. Since, they are already pre-trained detectors, fewer number of training set images were enough to perform object detection. Thousands of images would be needed if pre-trained network architectures were not used. Despite the smaller number of training images, Yolo and ResNet networks had higher detection rates.

More number of training images can be used to reduce the miss rates for these detectors. Diverse images should be included to improve the detection rates in any environmental or light conditions. If the position of the camera is placed at an increased height or placed on top of the parking lot, unoccluded images of vehicles can be obtained which would lead to better data quality. A better quality dataset can also lead to reduction of miss rates. The current position of the camera and viewing angle does not cover all the vehicles in the first four rows. Reducing the focal length would increase the viewing angle of the camera, thereby covering a greater number of vehicles. The IoU value used in this paper is 0.2 for acquiring parking occupancy. However, if unoccluded images are acquired then the bounding boxes would not be overlapped where a higher IoU value can be chosen to improve quality of detection.

Resnet networks were able to provide better detection results with minimal miss rates. However, the computation time is comparatively higher than other detectors. Computation time plays a vital role in providing real time vehicle occupancy. Therefore, ResNet50 is not suitable for real time vehicle occupancy despite its very minimal miss rates.

Table 1. Summary of results

Detector	Processing time in seconds	Log average miss rate	Positive detection rate
Yolo v2	< 1	0.68	96
GoogleNet	< 1	0.84	76
ResNet18	~ 1	0.06	100
ResNet50	~ 4	0.0	100

#### 6. Conclusion and future work

In this paper, real time vehicle occupancy using a thermal camera and deep learning was proposed. Deep learning object detection algorithms such as; Yolo, ResNet18, ResNet50 and Googlenet were implemented to identify multiple vehicles as they are dynamic and intelligent contemporary detectors. These results were compared with a template of parking spaces to acquire real time vehicle occupancy information. ResNet detectors performed better detection rates compared to other detectors. ResNet18 can be used to capture real-time vehicle occupancy as it uses less computational time and had higher detection rates. The future work can be focused on improving the detection rates of computationally efficient algorithms such as; Yolo or GoogleNet. This paper addresses the first step in identifying vehicle occupancy

information and the next step would be to automate the process of identifying vehicle occupancy suitable for any parking lot and provide navigational directions to probable empty parking spaces. This information will be fed to a smart parking application which can be utilized by the users.

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