A Smart Eco-System for Parking Detection Using Deep Learning and Big Data Analytics

Sai Nikhil Reddy Mettupally
Department of Computer Science
University of Alabama in Huntsville
Huntsville, USA
sm0143@uah.edu

Vineetha Menon
Department of Computer Science
University of Alabama in Huntsville
Huntsville, USA
Vineetha.Menon@uah.edu

***Abstract*—This work aims to conduct a comprehensive study on existing parking infrastructures and proposes intelligent parking solutions using novel Big Data Analytics with Deep Learning techniques. This research addresses the parking problems faced in most of the cities and growing colleges like University of Alabama in Huntsville (UAH). In this study, segmented images of parking spaces occupied by cars as well as available empty lots were extracted as spatial information and fed to a Convolutional Neural Network (CNN)-based Deep Learning framework. We expect this incorporation of spatial-temporal information would enhance the classification performance of CNNs. For proof-of-concept, performance will be validated on a free parking lot dataset-PKLot from Universidade Federal do Parana in Brazil. After desired classification performance is achieved, our robust CNN classification framework can be deployed on a cloud server to classify images in real-time. We also plan to release a parking-support mobile application (Android/IOS) that would display the real-time grid layout of empty and occupied parking spots using GPS information of the user. This app will be constantly updated based on parking information from the cloud-classifier. We expect that the outcome of this study will assist people in managing their time efficiently in finding their closest parking spot. It is also expected to ease the traffic flow and provide better parking management services.**

***Index Terms*—Parking, Big Data Analytics, Neural Networks, Smart City, IOT, Object Detection**

I. Introduction

With technological advances gearing us towards futuristic smart cities, everyday navigation, and parking are some of the significant applications that attract our attention. Even today, amidst our busy schedules and running chores, the necessity of parking the vehicle quickly in a parking lot has become an essential in the modern day lifestyle. There is a sheer necessity to assist and navigate the drivers towards the location of the nearest available empty parking space without having to search the entire parking lot. Also, it is equally important for the parking lot service providers to ensure a smooth and reliable parking service to the customers. Many have approached the parking space problem from the service provider end by displaying the number of vacant spaces in the parking lot to the customer [1]. This is helpful for the service provider to an extent, but the customer still has to explore the entire parking lot for an empty space. Few other service providers have implemented techniques that direct customer exactly to the empty parking space using a network of proximity sensors to detect an empty spot [2] [3].However, the former requires the parking lot to be installed with an array of in-ground sensors. Few popular sensor variants used in parking lot applications include infrared, ultrasonic or proximity sensors. Typically this involves installation of one sensor per parking space to detect its current status. If a car occupies the space, the sensor triggers and correspondingly the space is marked as occupied in the database. This method provides a partial solution to the parking nemesis of the customer, but for multiple reasons it is not the optimal solution for service providers:

- Deploying sensors is suitable for small sized parking lots but cannot be extended to suit large parking lots.
- Installation costs of the sensors and the supporting ecosystem is very high.
- Maintenance of the sensors is difficult due to factors like inclement weather, physical damage with the possibility of cars running over them.
- Furthermore, the other issues that are rarely addressed include the sensors' susceptibility to physical tampering and Cybersecurity concerns.
- Rolling out software updates to the sensors is time consuming as there are multiple endpoints to consider in this solution.

The above mentioned short-comings are addressed using image processing techniques to extract the details of empty spaces from the parking lot image [4] [5] [6]. In [7] the authors have listed 5 methods in parking space detection and concluded that video/image based detection yields better results than the aforementioned proximity sensor-based detection techniques. Therefore, this work provides an extension to the above argument in [7] and motivation that software-based solutions can indeed trump hardware-dependent solutions. For this we devise a software-based solution to address the parking nemesis through a smart framework that employs the culmination of Computer Vision, Big Data Analytics and Neural Network paradigms. Our proposed method is designed to be cost-effective, scalable for the service provider and at the same time intuitive and user-friendly to the customer. We define our

978-1-7281-0137-8/19/$31.00 ©2019 IEEE

unique parking solution not as an individual component but envision it a part of an ecosystem which consists of

- a high-resolution camera
- a robust object classification and detection model
- a fault tolerant, scalable back-end server
- a mobile application

For data acquisition, existing visual sensors i.e., video cameras that are commonly employed for parking lot monitoring is considered. This allows data to be collected periodically at no additional cost to the service provider. The camera is mounted on top of a building adjacent to the parking lot that captures the real-time video of the parking lot. This real-time video-feed will be sent as the input to a Convolutional Neural Network (CNN), that detects the cars and their locations in the parking lot. The data that has been processed is then sent to the mobile application that alerts the user of the vacant parking spaces in their vicinity. We believe that this smart parking ecosystem will be one of the key elements in shaping the Smart city planning and parking scenario. It has been proven that feature extraction from images and videos using CNNs are better than that of the other machine learning models. Recent advances in the field of deep learning have paved way for state-of-the-art object detection in various applications like face recognition [8], automatic traffic signals [9], iris detection [10]. In the present work, we have chosen CNNs as the base model and its different variants to improve the detection and classification performance of the model.

II. Proposed Methods

In this section, we discuss two CNN-based supervised learning models that were used in our parking detection and classification framework.

A. *CNNs-based supervised learning model*

Our parking framework consists of a four-layer CNN that was trained on the segmented images from the PKLot dataset. These segmented images from the PKLot dataset were resized to 64 x 64 images that contains images of both cars and empty parking spots. These images were used to train the CNN for a supervised classification model as shown in Fig. 1. The ultimate goal of this model is to enhance the ability to distinguish a car from an empty parking spot. The model used here has four layers for the four operations performed on the input image. The layers are arranged in the standard convolution-pooling-flattening-full connection fashion.

B. *Mask R-CNN*

While CNNs have proved that they perform well in object detection, they tend to perform best when only a single object exists in the image. This is an ideal scenario when there is a distinct difference between the foreground target/object and the background image. Target/object detection becomes a highly challenging task with the increase in the number of targets to be detected. Any form of data learning performed to achieve this purpose must account for factors such as the inherent data/target attributes and the interplay of the targets with their surrounding environmental factors. Therefore, in order to enhance multiple target/object detection scenario, it is essential that we integrate information from different known data attributes along with their spatial images such as timestamp, location or orientation of the image as well as background versus foreground information. This is achieved with the help of Regional Convolutional Neural Network (R-CNN) model. The R-CNN model [11] outlines and suggests a set of regions in the image that closely corresponds to the object. These regional images extracted contain important local information for better object detection and are sent as an input to a modified version of the AlexNet [12] neural network. Over the last 5 years researchers have improved the performance of R-CNNs through introduction of related architectural variations of CNN base model such as Fast R-CNN [13], Faster R-CNN [14] and Mask R-CNN [15]. Since our application aims to focus on real-time parking detection, we have employed faster R-CNN to expedite the process of regional image generation and extraction. Finally, Mask R-CNN proposed by the Facebook AI Research (FAIR) group was used to was used to extend object detection performed by Faster R-CNN to pixel level segmentation by generating masks of the object. We denote our proposed model as depicted in Fig 2 as Fast Mask R-CNN (FMR-CNN) model. Thus, our proposed CNN framework FMR-CNN that uses the Mask-RCNN version provides a broad spectrum of knowledge discovery, i.e., from course regional/ neighborhood information to finer pixel-level object information. In this paper, we have used Mask R-CNN built on FPN (Feature Pyramid Network) and ResNet101 backbone architecture with pre-trained weights from the COCO dataset for the detection of cars in the parking lot. FPN uses a top-down architecture with lateral connections to build an in-network feature pyramid from a single-scale input [15].

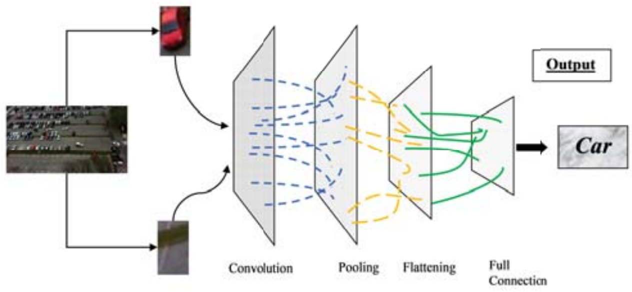

Fig. 1. Basic CNN architecture depicting the proposed object detection.

III. Results

A. *Dataset Description*

1) PKLot Dataset: To evaluate the effectiveness of our proposed FMR-CNN model, we have used the PKLot Dataset provided by the Federal University of Parana [16]. The dataset consists of 12,417 parking lot images captured in different weather conditions (sunny, rainy and overcast) and are entirely

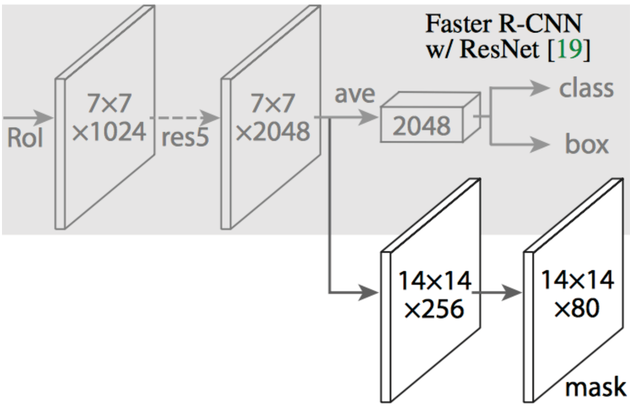

Fig. 2. Architecture of Mask R-CNN with ResNet convolutional backbone [11]

acquired from the parking lots in Federal University of Parana (UFPR) and Pontifical Catholic University of Parana (PUCPR) in Brazil. 695,899 images of individual parking spaces are segmented from the parking lot images and are manually labeled.

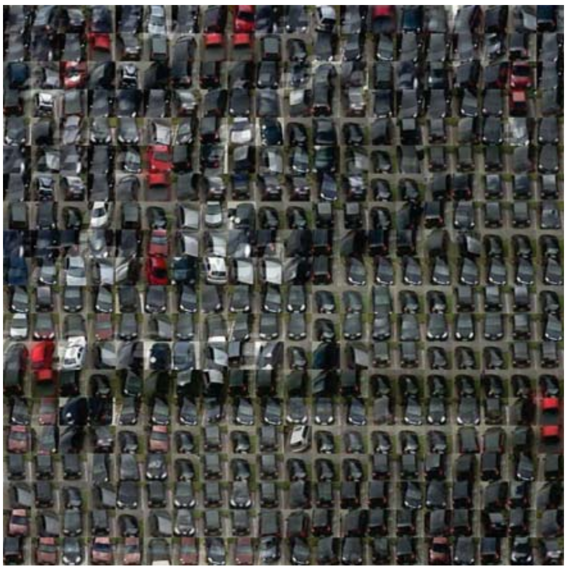

Fig. 3. Mosaic of the segmented car images from the PKLot dataset

For experimental validation, we have used a subset of 6100 images from the entire dataset that are seen in Fig. 3. for the purpose of training and testing the model. To replicate the real-world scenario, our goal is to achieve a good performance by training the model with minimum number of images. Hence, our training set had 1000 images and validation set had 5098 images. The CNN is trained on 1000 segmented images consisting of 102 empty parking space images and 898 occupied parking space images and is validated with 5098 images comprising of 1903 empty parking space images and 3195 occupied parking space images. Our proposed conventional CNN model for parking application demonstrated superior performance with an average accuracy of 87.69% in identification of cars present in the parking lot.

2) COCO Dataset: COCO stands for Common Objects in COntext [17]. It was developed by Microsoft with the goal of advancing the state-of-the-art in object recognition. The COCO dataset contains 80 common object categories with 2,500,000 labeled instances in 328,000 images.

For this dataset, we explored on extending our Mask R-CNN framework built using FPN and ResNet101 backbone. This is accomplished by loading the pre-trained COCO weights on to our existing FMR-CNN model [18]. The main idea behind using pre-trained weights is to reduce the time taken to train our model. We perform a comparative study on the effects of changing the detection threshold.

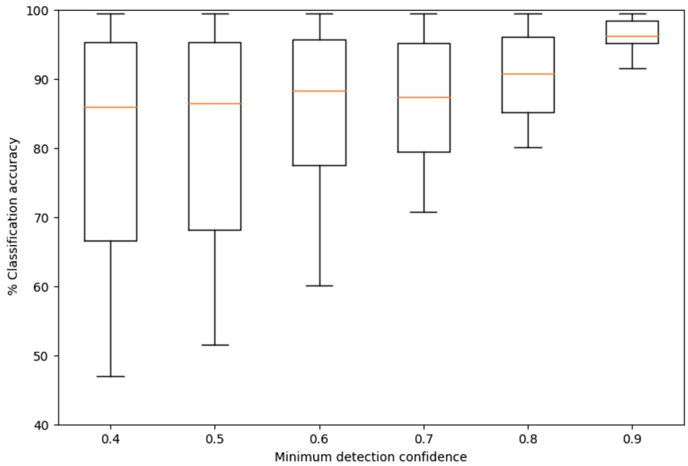

Fig. 4. Minimum detection confidence vs % Classification accuracy. The red line denoted the average accuracy for each detection confidence value.

By varying the minimum detection confidence parameter, we see from Fig 4. that the average accuracy with which the cars are detected showed an increasing trend. From Fig 4., we can also observe the respective minimum and maximum detection range of accuracies for each value of detection confidence. We set the minimum detection confidence parameter to 0.8 (or 80% confidence) to define and ensure that the detected object is indeed a car. Choosing the right value for minimum detection confidence parameter is crucial to the reduction of false positives. This is helpful in reducing the false positives. Fig 5. below illustrates the an instance of detection of cars on one of the parking lot images from the PKLot dataset.

TABLE I
PERFORMANCE STATISTICS OF THE CNN AND FMR-CNN MODELS

CNN Model	Accuracy	Computational time (in seconds)
4-layer CNN	87.69%	212.77
FMR-CNN	91.9%	57.03

From Table I we see that FMR-CNN is computationally faster than the conventional CNN model. Therefore, from our experiments, we conclude that our proposed FMR-CNN model

Fig. 5. Detection of cars in the parking lot using FMR-CNN model on an image from the PKLot dataset

showed great promise and was able to detect the cars present in the parking lot with a mean average accuracy of 91.9%.

IV. Conclusion

In this paper, we propose a revolutionary premise for a cost effective and user-friendly parking eco-system that uses Computer Vision and Deep Learning to guide the user to the nearest parking space in the parking lot with the help of a mobile application. The primary focus of the work lies in reducing the model training time and outlining the classification model that is used to detect the vehicles. CNNs are employed to build a supervised classification model that detects the cars present in the parking lot. For this, we have designed a new FMR-CNN model that detects multiple cars in an image with an average accuracy of 92% which outperformed the traditional 4-layer CNN model's average car-detection accuracy of 88%. Experimental results demonstrate that our proposed FMR-CNN model is viable and effective for parking detection application than the standard CNN models.

V. Future Scope

Further, the work done in this paper can be extended to process real-time video from a camera. Performance study of the model could be done based on the fixed or multi-view camera angles. A mobile application on Android and iOS platforms could be developed displaying the real-time parking information. On a global scale, user can get the vacant parking space information from all the parking lots equipped with this system. Depending upon the location of the parking lot, service provider can choose to introduce subscription plans to reserve parking spaces. Google maps can be integrated to guide users to the nearest empty spot once they enter the specified parking lot.

References

[1] Ming-Yee Chiu; Depommier, R.; Spindler, T.; , "An embedded real-time vision system for 24-hour indoor/outdoor car-counting applications," Pattern Recognition, 2004.

[2] Tang. VWS, Zheng. Y, Cao. J, An intelligent car park management system based on wireless sensor networks, SPCA06 : 1st International Symposium on Pervasive Computing and Applications : August 3-5, 2006 Urumchi, Xinjiang, P.R. China, p. 65-70.

[3] J. Yang, J. Portilla and T. Riesgo, "Smart parking service based on Wireless Sensor Networks," IECON 2012 - 38th Annual Conference on IEEE Industrial Electronics Society, Montreal, QC, 2012, pp. 6029-6034.

[4] Tschentscher, M.; Neuhausen, M. Video-based parking space detection. In Proceedings of the Forum Bauinformatik, Bochum, Germany, 2626 September 2012; pp. 159166.

[5] K. Ueda, I. Horiba, K. Ikeda, H. Onodera, and S. Ozawa, (1991). An algorithm for detecting parking cars by the use of picture processing (1981), IEICE Trans. Information and Systems.vol.J74-D-I1. IO, pp. 1379-1389.

[6] N. Bibi, M. N. Majid, H. Dawood and P. Guo, "Automatic Parking Space Detection System," 2017 2nd International Conference on Multimedia and Image Processing (ICMIP), Wuhan, 2017, pp. 11-15.

[7] Z. Bin, J. Dalin, W. Fang and W. Tingting, "A design of parking space detector based on video image," 2009 9th International Conference on Electronic Measurement & Instruments, Beijing, 2009, pp. 2-253-2-256.

[8] Khalajzadeh, Hurieh et al. Face Recognition Using Convolutional Neural Network and Simple Logistic Classifier. (2014).

[9] Mller, Julian and Klaus C. J. Dietmayer. Detecting Traffic Lights by Single Shot Detection. 2018 21st International Conference on Intelligent Transportation Systems (ITSC) (2018): 266-273.

[10] L. He, H. Li, F. Liu, N. Liu, Z. Sun and Z. He, "Multi-patch convolution neural network for iris liveness detection," 2016 IEEE 8th International Conference on Biometrics Theory, Applications and Systems (BTAS), Niagara Falls, NY, 2016, pp. 1-7. doi: 10.1109/BTAS.2016.7791186

[11] Girshick, Ross et al. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. 2014 IEEE Conference on Computer Vision and Pattern Recognition (2014): arXiv:1311.2524v5 [cs.CV]

[12] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. 2012. ImageNet classification with deep convolutional neural networks. In Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume 1 (NIPS'12), F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger (Eds.), Vol. 1. Curran Associates Inc., USA, 1097-1105.

[13] Girshick, Ross. Fast R-CNN. 2015 IEEE International Conference on Computer Vision (ICCV) (2015): arXiv:1504.08083v2 [cs.CV]

[14] Ren, Shaoqing et al. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence 39.6 (2017): 11371149. arXiv:1506.01497v3 [cs.CV]

[15] He, Kaiming et al. Mask R-CNN. 2017 IEEE International Conference on Computer Vision (ICCV) (2017): arXiv:1703.06870v3 [cs.CV]

[16] Almeida, P., Oliveira, L. S., Silva Jr, E., Britto Jr, A., Koerich, A., PKLot A robust dataset for parking lot classification, Expert Systems with Applications, 42(11):4937-4949, 2015.

[17] Tsung-Yi Lin, Michael Maire, Serge J. Belongie, Lubomir D. Bourdev, Ross B. Girshick, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollar,C. Lawrence Zitnick, Microsoft COCO: Common Objects in Context, 2014, arXiv:1405.0312 [cs.CV]

[18] Working code forked from Mask R-CNN for Object Detection and Segmentation, Waleed Abdulla, Github(matterport/MASK-RCNN)