Convolutional Neural Network for Parking Slots Detection

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Abstract

With the rapid growth of transport number on our streets, the need for finding a vacant parking spot today could most of the time be problematic, but even more in the coming future. Smart parking solutions have proved their usefulness for the localization of unoccupied parking spots. Nowadays, surveillance cameras can provide more advanced solutions for smart cities by finding vacant parking spots and providing cars safety in the public parking area. Based on the analysis, Google Cloud Vision technology has been selected to develop a cyber-physical system for smart parking based on computer vision technology. Moreover, a new model based on the fine-tuned convolutional neural network has been developed to detect empty and occupied slots in the parking lot images collected from the KhNUParking dataset. Based on the achieved results, the performance of parking lots' detections can be simplified, and its accuracy improved. The Google Cloud Vision technology as parking slots detector and a pre-trained convolutional neural network as a feature extractor and a classifier were selected to develop a cyber-physical system for smart parking. As a result of the computational investigation, the proposed fine-tuned CNN managed to process 66 parking slots in roughly 0.14 seconds on a single GPU with an accuracy of 85.4%, demonstrating decent performance and practical value. Overall, all considered approaches contain strengths and weaknesses and might be applied to the task of parking slots detection depending on the number of images, CCTV angle, and weather conditions.

Keywords [1]

Video-image processing, smart parking, deep learning, convolutional neural network, OpenCV, Google Cloud Vision

1. Introduction

In recent years, the issue of creating smart parking has become highly essential, especially in large cities. As the number of cars has rapidly increased over the last few years (see Fig. 1), so does the need for parking spaces and search facilities. Assuming that the average driver spends 20 minutes searching for such a place every day, about 120 hours a year could be spent on something more useful.

As shown in Fig. 1, most vehicles entering Ukraine have been newly imported automobiles (red part of the column) and used cars from Europe and the USA (green part of the column). At the same time, it is noticeable that from 2016 to 2020, the import of new vehicles remains at about the same level, but the share of imports of used cars is gradually increasing. Such an outcome was due to changes in the legislation on customs clearance of vehicles imported from abroad on Nov. 25, 2018; a law was passed to simplify the procedure for customs clearance of used cars imported from abroad

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[1]. Nowadays, there are many smart parking projects, but ready-for-use examples can be counted on the fingers of one hand, and information about the cost-effective aspect of their implementation is generally minimal. It should be noted that when designing such tools, the most significant financial part of the development is born by the software, not hardware. After considering and comparing different parking detection techniques [2], a conclusion has been made that the method of smart parking using visual surveillance based on an external closed-circuit television (CCTV) is much more effective than others, considering most of the factors considered.

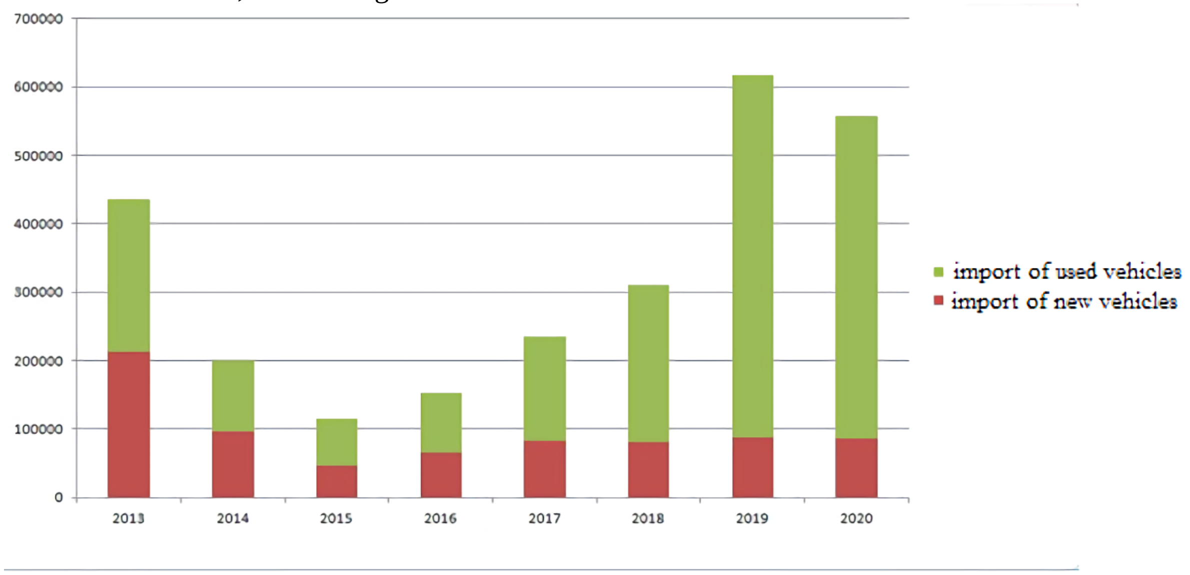

Figure 1: Increase in vehicle numbers in Ukraine

Information technologies have been widely used to visualize civilian infrastructure using simple and affordable video surveillance cameras, i.e., CCTVs. The same CCTVs can be used to detect the occupied and empty slots in automobile parking lots. Videos and images obtained from such cameras are processed and analyzed with computer vision (CV) techniques and tools. However, two challenges prevent the widespread use of CV means for occupancy detection.

The first issue implies the low performance of detecting occupied and vacant parking slots by CV against sensor camcorders or ordinary manual counting [3]. Generally, the low accuracy of CV-based approaches happens due to various factors, such as the different appearance of vehicles, the impact of the environment on images (like shadows, bright sunlight, or fog), occlusion by other vehicles (or stationary objects), visual distortion due to the inspection of cameras at an acute angle.

The delimitation of parking slots in videos or images is another challenge of vision-based methods. A parking area can be covered by numerous CCTVs, yet the boundaries of the parking lot may change over time due to law enforcement or municipal reasons. In addition to this, marking manually every parking space in videos and images is a time-consuming task and may cause many technical mistakes. Accordingly, the use of automatic means and methods for delineating the boundaries of parking spaces is highly relevant for parking solutions based on intelligent information technologies [4]. Consequently, in order to achieve the goal of the study, the following tasks must be completed:

1. To search and analyze up-to-date technologies for image and video processing based on modern CV methods and means.
2. To select the most appropriate technology to create a cyber-physical system for smart parking based on the outdoor surveillance camera of the university parking lot.
3. To develop an information model for parking slots detection and vehicle identification.
4. To validate the developed model in terms of its practical value.

2. Related works

The scientific community has actively investigated and proposed novel CV methods and approaches to identifying and demarcating parking areas. Traditional visual-based techniques for detecting parking slots are divided into line-based [5] and marking-point-based [6]. Line-based approaches first construct visible lines in an image around a region of interest (ROI) using various CV features, such as the Canny edge detector [7], Laplacian operator [8], and Haar Cascade [9]. Next, the parameters of the detected lines are predicted using a line fitting algorithm to draw boundaries around the ROI. Similar to line-based approaches, marking-point-based ones seek for marking points in an image around an ROI using, for example, Harris edge detector [10] or boosting decision tree [11], and then use a pattern matching technique [12] or combining line detection [13] to locate a targeted parking space. Even though such traditional techniques of detecting parking spaces provide decent results, they are susceptible to changes in the environment and, therefore, not applicable to component cases of delimitation of parking areas.

Overall, table 1 presents decent studies that have been conducted over the past years to find the best approach for parking slots detection and vehicle recognition.

Table 1
Analysis of existing computer vision approaches for smart parking

#	Year	Algorithm / Model	Advantages	Disadvantages
[12]	2018	Deep convolutional neural network, OpenCV	This approach utilizes coordinates of every parking slot requiring relatively less computational power.	The features obtained from the benchmark dataset may not be practical for recognizing real outdoor parking lot.
[9]	2019	Haar Cascade, XGBoost	This ensemble approach allows identifying a vehicle or a parking slot from any angle of view; the use of imposed features ensures the detection accuracy of an individual vehicle of roughly 100%.	In multiple-vehicle detection, the superimposed features sometimes do not distinguish between similar edges of objects, leading to the detection of two vehicles as one.
[13]	2020	Faster R-Convolutional neural network	The hyperparameters of the neural network are fine-tuned according to the characteristics of the parking spaces, leading to a high precision rate of 99.63%.	The network may miss some parking spaces, as the entry point markings are faint, and the parking space is less than the threshold.
[14]	2020	Hough Transform, OpenCV	This approach provides a maximum recognition accuracy of about 100% by the fixed CCTV position and constant light intensity).	Even minor changes in light and shadows might considerably worsen the classification results.
[15]	2021	Long short-term memory	High-level prediction of empty parking spaces using CV technology and the real-time car parking data.	The detection algorithm is adapted to a specific parking space; even minor changes within the parking lot can adversely affect classification accuracy.
[16]	2022	Mask R-Convolutional neural network, OpenCV	A scalable and relatively inexpensive system can detect empty parking spaces based on video and image data.	The performance results of this approach highly depend on the surveillance camera and computing device.

As can be seen from Table 1, a deep learning (DL) approach, particularly deep convolutional neural networks (CNNs), has been most frequently used over the past five years and has shown the most robust recognition of parking lots, among other approaches. For example, DeepPS [12] is the first multi-module information system based on DL algorithms for identifying parking spaces. This system is based on two visual-based technologies: the well-known OpenCV library to describe the marking points in an image around ROI and CNN to identify the target features of vehicles in an image and match the paired marking points with the identified features. Overall, ensemble approaches based on deep neural networks demonstrate the best performance in detecting parking slots and vehicles in different environmental conditions.

Therefore, considering the abovementioned analysis, two visual-based technologies were defined as the most effective for parking lot detection – OpenCV and CNN.

2.1. OpenCV Computer Vision Library + CNN

Over the past decades, the OpenCV computer vision library [18] has become the leading technology in the image processing domain. This tool set serves as a so-called infrastructure for applying CV techniques in information systems. OpenCV is used, among other things, to resize input images, convert them to vector form, and detect the features of target objects in the image. At the same time, one of the most popular approaches to detecting features in the image today is DL, in particular, CNN [19]-[21].

The CNN model combines many functional operations that transmit the input image as feature vectors into the resulting data to estimate the belonging of the identified objects to predefined classes. The CNN architecture utilized in this study is from the authors' previous work [22] and is depicted in Fig. 2.

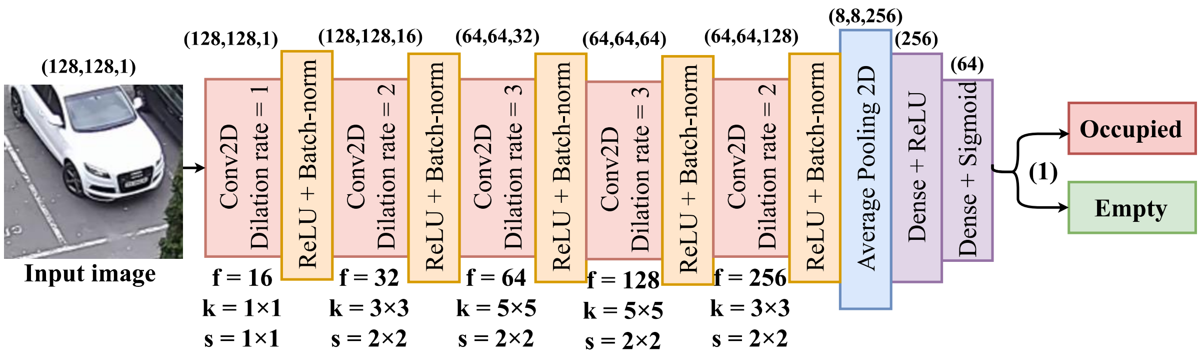

Figure 2: The scheme of convolutional neural network used in this work

According to the classification results in [23], we conclude that combining the GCV API system and OpenCV + CNN tools may achieve more robust performance and higher classification accuracy.

2.2. Google Cloud Vision API (GCV API)

Another equally well-known image recognition technology is the Google Cloud Vision API (GCV API) [24]. The GCV API is a de facto set of prepared machine learning models and algorithms that service users can quickly implement to meet their business needs. The principle of the GCV API is to perform two steps: 1) assigning labels to the original image; 2) automatic recognition of objects in the image by predefined classes. The GCV API is a universal classifier that identifies various moving and still objects in an image.

In [23], we conducted a preliminary experiment: ten images were used from the video surveillance camera of one of the parking lots of Khmelnytskyi National University. The images were preliminarily prepared: the contours were cropped to bring the focus as close as possible to the location of the cars. In addition, the objects in the image were magnified to increase the likelihood of finding the object.

The experiment was to test the same image using two of the most popular image recognition technologies. The object identification results on the target image, performed using OpenCV + CNN and GCV API technologies, are shown in Fig. 3.

Fig. 3 shows that GCV API technology coped much better with the task of identifying cars on the image (Fig. 3a) than OpenCV + CNN technology (Fig. 3b).

(a) (b)

Figure 3: Identified objects on the target image that correspond to the searched cars, found by: (a) – OpenCV + CNN, (b) – GCV API [23]

Hence, the GCV API system as a parking slots detector and a pre-trained CNN as a feature extractor were chosen to develop a cyber-physical system for smart parking.

3. The model

The authors compiled Dataset (KhNUParking) from the collected images extracted from an external closed-circuit television (CCTV). The CCTV was installed on Campus 3 of Khmelnytskyi National University, Ukraine. The images show parking spaces of the outdoor parking lot between campuses 3 and 4 of the university (Fig. 4).

(a) (b)

Figure 4: The samples of the KhNUParking dataset presenting targeted parking spaces: (a) – almost all parking lots are empty, (b) – nearly all are fully occupied

The initial KhNUParking was collected of 100 images extracted from a CCTV, each of which was 853 × 480 pixels, and then was split into training (70%) and validation (30%) subsets. An additional subset of 100 images was created to test the classification models. Furthermore, actual annotations of the parking slots, ground boxes (33 slots), and the occupancy (3300) were employed to assess the proposed approach’s accuracy.

PKLot: a subset of 390 randomly sampled images of 1280 × 720 pixels was collected from the PKLot dataset [25]. It must be noted that in the original PKLot dataset, parked vehicles are displayed from up to down.

Experimental setup: all computational experiments were performed on the Python v3.8 stack with Keras as the back end. The calculations were executed on 8-core Ryzen 2700 and a single GPU card GeForce GTX1080 with 8 GB of memory.

Methodology: the proposed approach for CV technology is depicted in Fig. 5.

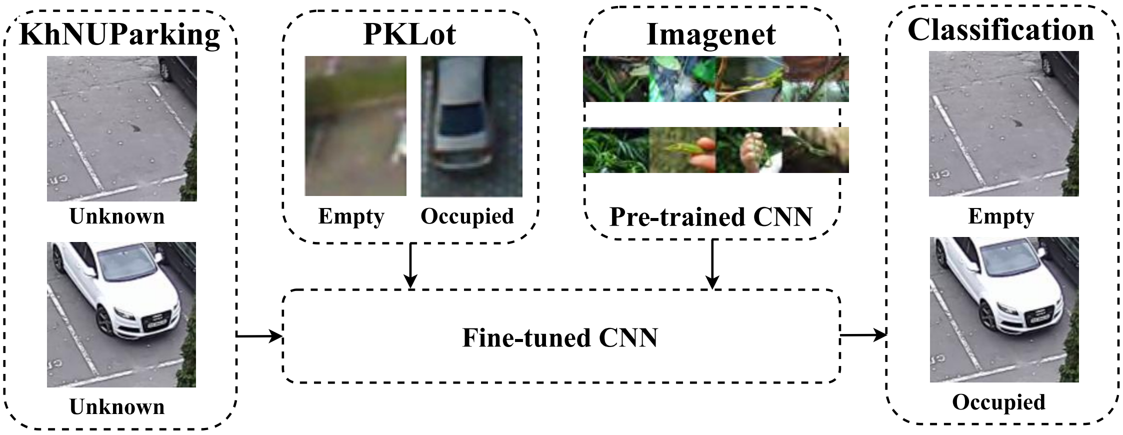

Figure 5: The proposed approach for smart parking cyber-physical system

In this work, we utilized a neural network model based on pre-trained CNN as a feature extractor and a two-layer perceptron as a classification module. The pre-trained CNN contained 1000 classes (pre-trained with the ImageNet dataset). To prepare the model for detecting occupied and empty parking spaces, the last fully connected layers in the network were replaced with two classes that correspond to "Empty" or "Occupied." In this work, the testing models were evaluated by several statistical indicators and run-time, an average time in seconds to read images from the hard disk and crop them. Statistical measurements used in this study are defined as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \tag{1}$$

$$\text{Precision} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{3}$$

$$F_1 = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{4}$$

where TP represents true positive cases in the testing dataset, TN stands for true negative cases, FN denotes false positive, and FN represents false negative cases.

The data augmentation technique was also performed on the fine-tuning dataset to reduce over-fitting.

Two transformations were applied: 1) reflection along X and Y axes and 2) change of the X and Y scales of the images. Furthermore, the input images were resized to 128 × 128 to fit the input of the fine-tuned CNN.

4. Experiments and Results

The network was pre-trained with a stochastic gradient descent with a momentum of 0.8, a learning rate of 0.005, and a batch size of 64; training epochs were set to 20. The pre-training process took roughly 50 minutes on a single GPU. Fig. 6 shows the training and validation accuracy and loss curves.

The prepared fine-tuned CNN was tested on the set of 100 KhNUParking images in the following matter. At first, in each of 100 images, 33 individual parking slots were cropped and then passed to the fine-tuned CNN to perform the classification task.

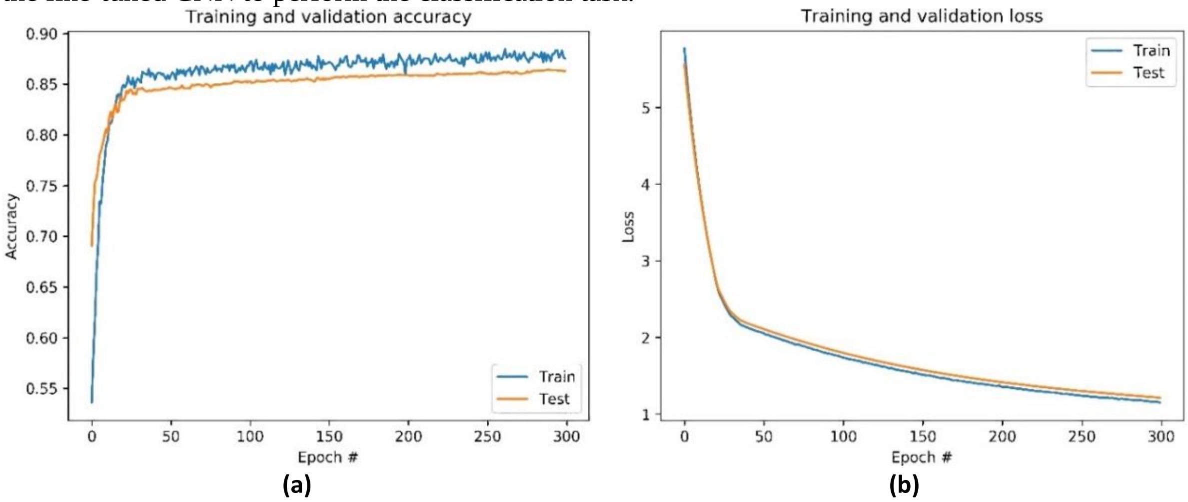

Figure 6: Training and validation curves of the pre-training procedure: (a) – accuracy, (b) – loss function

The actual samples of the KhNUParking dataset contained the status of 3300 occupied/empty spaces and 33 ground boxes of the parking slots.

Here, the delineations of parking slots are presented as the so-called bounding boxes that also crop the individual parking slots.

A bounding box is determined by [x, y, w, h], where [x, y] – the coordinates of the middle of the boxes, and [w, h] – the width and height. Fig. 7 presents the classification results obtained by the testing dataset.

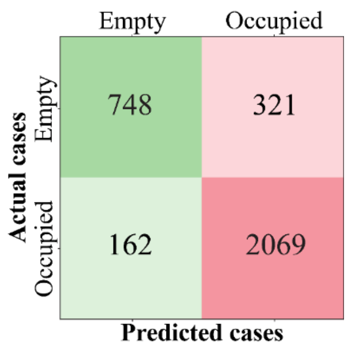

Figure 7: The confusion matrix of the prediction results

As it is seen from Fig. 7, 748 empty parking spaces and 2069 occupied parking lots were correctly identified; meanwhile, 321 vacant lots were classified wrongly, and 162 occupied spaces were recognized as open. So, the overall classification accuracy was 85.34%. According to the obtained classification results, the proposed fine-tuned CNN makes more mistakes and thus less accurate in identifying empty parking spaces.

Upon visualizing a few of the wrongly identified parking spaces in Fig. 8, it was observed that those parking lots mostly contained parts of vehicles, people, or other objects inside the image crop. Finally, Fin. 9 shows the visual representation of the classified parking slots.

Several models, namely AlexNet [19], VGG-16 [20], and MobileNetV2 [21], were compared with the fined-tuned CNN in terms of their efficiency and accuracies.

The classification results obtained from all models are shown in Table 2.

Figure 8: A few falsely classified parking spaces with their occupied scores

Figure 9: The visualization sample of the parking lot: red color represents the occupied slots, green color represents empty slots

Table 2
The comparison of well-known neural network architectures with our proposed fine-tuned convolutional neural network based on the KhNUParking dataset

Approach	Accuracy	Precision	Recall	F_1	Time, seconds
AlexNet [19]	0.777	0.820	0.858	0.839	0.49
VGG-16 [20]	0.843	**0.878**	0.891	0.885	0.71
MobileNetV2 [21]	0.852	0.863	**0.928**	0.895	0.52
GCV API [24]	0.673	0.767	0.741	0.754	0.22
Our fine-tuned CNN	**0.854**	0.866	0.927	**0.896**	**0.14**

Table 2 presents the values of statistical measurements (1)-(4) (validity) and run-time on GPU (efficiency) obtained by comparing approaches. As it is seen from the table, the generalizing ability of all models is high enough for this quality of parking spaces, yet there are some differences in indicators among the models. The proposed fine-tuned CNN performed better in classification accuracy (85.4%) and F_1-score (89.6%), surpassing the analogs by at least 0.15% and 0.09%, respectively. At the same time, the VGG-16 model achieved the highest precision (87.8%), surpassing our model by 1.24%, while MobileNetV2 scored the highest recall (92.8%), surpassing our model by 0.09%. As for run-time, our fine-tuned CNN required the least computational time, scoring only 0.14 seconds to read the images from the hard disk.

Google Cloud Vision showed worse performance than the analogs in these experiments yet retained appropriate generalizing ability over diverse parking spaces. In conclusion, all considered approaches contain strengths and weaknesses and might be applied to the task of parking slots detection depending on the number of images, CCTV angle, and weather conditions.

Overall, the proposed fine-tuned CNN could process 66 parking slots in roughly 0.14 seconds on a single GPU with an accuracy of 85.4%, demonstrating decent performance and practical value.

5. Conclusions

Therefore, during the study, an analysis of information technologies for image recognition based on computer vision was conducted. Based on the analysis, Google Cloud Vision technology has been selected to develop a cyber-physical system for smart parking based on computer vision technology. A new model based on the fine-tuned convolutional neural network has been developed to detect empty and occupied slots in the parking lot images collected from the KhNUParking dataset. Based on the achieved results, the performance of parking lots' detections can be simplified, and its accuracy improved. It was also concluded that the Google Cloud Vision technology as parking slots detector and a pre-trained convolutional neural network as a feature extractor and classification were decided to develop a cyber-physical system for smart parking. As a result of the computational investigation, the proposed fine-tuned CNN managed to process 66 parking slots in roughly 0.14 seconds on a single GPU with an accuracy of 85.4%, demonstrating decent performance and practical value.

Further investigation will be devoted to developing the server- and client-based parts as a mobile app that tracks the availability of vacant places at the university's parking lot.

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