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# Detection parking Spaces by using the ResNet50 Algorithm

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## ABSTRACT

*Finding an empty parking space in a crowded area is very stressful due to congestion. The absence of empty space leads to fatigue before the main activity, increased fuel consumption, which leads to increased pollution, and increased traffic due to the search for empty space. Therefore, it was necessary to have a system that would help drivers know the condition of each parking space. Empty or occupied with a vehicle. Where empty and occupied spaces are calculated and determined. The system displays on the screen at a convenient location in the parking lot a map to guide the driver to vacant positions and a warning if all positions are occupied. All this is done through images taken from the surveillance cameras in the parking lot. We find that the advantages of using vision-based systems over other existing systems are threefold. First There is no need to update the infrastructure of the parking lot, provided that the place is equipped with CCTV cameras that monitor the parking spaces covering the entire place. Secondly, camera-based systems give the exact location i.e. a detailed map of the vacant car parks which are good and necessary vacant lots. Third, camera-based methods are highly applicable in street parking spaces and residential areas.*

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## 1. Introduction

The demand for parking increases due to the decrease in available parking spaces in urban cities due to the increased demand for land [1]. Thus, the presence of an automatic parking monitoring system helps in directing drivers to an empty parking space at the right time [2]. This system detects the status of the positions, whether they are occupied or empty. The detection process must be reliable, regardless of external constraints such as weather conditions, vehicle, type, or lighting [3]. Moreover, the solution is implemented with minimal cost in

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terms of installation and maintenance. Most of the current solutions rely on sensors such as ultrasonic or magnetic sensors to indicate the status of parking lots, [4] [5] It is better to develop automatic parking space detection such a system that reduces human effort and increases the ability to work in high efficiency to avoid any waste of time. [6] Parking techniques are an indispensable part of facilitating traffic, congestion, and accident-free cars. Other benefits include lower fuel burn emissions and reduced driver waiting time. This information stimulated the research community to research and develop parking technologies, and the discovery of parking spaces and their real-time occupancy determination became one of the most important design elements of future smart cities. [7] Finding empty parking spaces in urban areas often takes a long time. Effective guidance systems can help drivers reduce the time they search for available parking spaces. Computer vision technologies are a better alternative than systems that use sensors, where footage from car parking surveillance cameras can be used to discover vacant parking spaces because sensor systems are expensive due to hardware and installation requirements and need periodic maintenance, as well as do not provide a detailed occupancy map of the car park to infer the empty space [6].

## 2. Background and related work

Acharya et al. (2018) In [7], the authors presented a robust framework for parking occupancy detection using a deep CNN and a binary support vector machine (SVM) classifier to detect outdoor parking space occupancy from images. The classifier was trained and tested on public data sets (PKLot) that have different lighting and climatic conditions. Then, the performance of transfer learning (the ability to generalize results to a new data set) was evaluated on a special data set created for this research. The accuracy rate obtained by the proposed method is 99.6%, and 96.7% for the public data set and the private data set respectively, which indicates the great potential of this method to provide a low-cost and reliable solution for PGI systems in outdoor environments.

Siddiqui et al. (2020) In [8], proposed a DELM-based approach using deep machine learning through sensors installed in designated parking lots and using machine learning techniques where information is collected through sensors in different parking spaces to obtain information about the free space and occupied using a neural network model. Good reliability and marginal error rate are achieved in this way, reducing uncertainty. We used neural networks for deep learning which. This method achieved the highest accuracy rate obtained of 94.37% during training and 91.25% when validating.

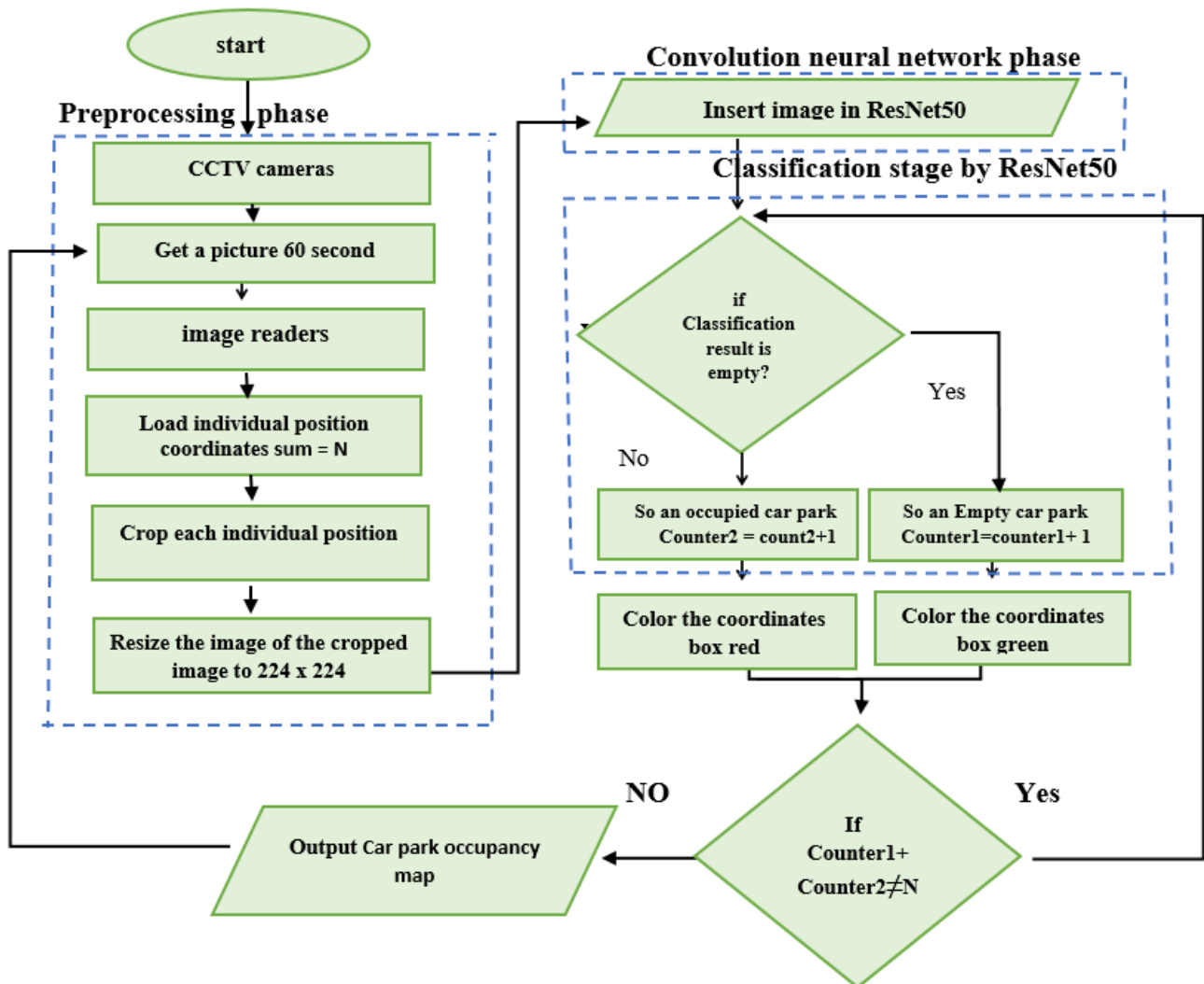
Wei Li et al. (2020) In [9], DCNN model proposed an empty parking detection method based on deep learning and based on parking signs, the VPS-Net algorithm showed that it can detect many empty parking spaces with an accuracy of 99.63%. The retrieval rate is 99.31% and using ps2.0, this algorithm has satisfactory generalizability within the PSV dataset. PSV is a promising three-part technology, and it should be noted that the custom DCNN model not only achieves good accuracy but also consumes the least time in image processing and uses the fewest number of parameters.

Albertus Farley et al (2020) In [10], evaluated 4 algorithms that were used in this work: AlexNet, LeNet, Mini AlexNet, and Mini LeNet. The training and validation sets were combined which produced the CNRPark + Ext which is a dataset. The research results proved that the proposed mAlexNet method has classification rates higher than 93.15% and a processing time of 0.5 seconds per parking space.

## 3. Proposed System

This system uses a parking monitoring camera installed in a parking lot, which is preferably at the height of the light pole, in order to avoid blockage. The image taken from these cameras every minute is used as an input to the system, which contains the coordinates for each individual parking lot, which is preset manually. The system cuts individual parking lot images and they are fed into a CNN (ResNet50) network, which is pre-trained on empty and occupied parking space images. The output of ResNet50 is the rating of all individual parking spaces. If it is empty or occupied by a car, the system calculates the empty and occupied places and outputs a map so that it is displayed on a screen in a suitable place in the parking lot to guide drivers to the empty place and if it is not

available. Empty space alerting drivers not to enter the parking lot The proposed system is illustrated by the flowchart (1)



**Figure (1):** The block for the proposed system (Parking Spaces Detection)

### 3.1 Pre Processing Stage

A pre-processing step is applied to the input image before it is used in the proposed system, and these steps consist of the following:

Get position images from CCTV cameras. Determine the coordinates of the individual parking lot (parking layout). Crop the individual parking lot in the image. And change the size of the cropped image in proportion to the algorithm used by the system (ResNet50) These steps are shown in Figure 2.

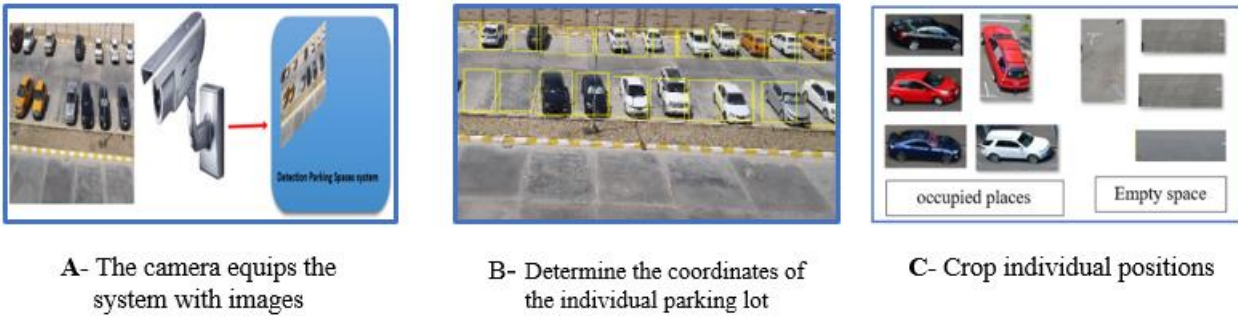


Figure (2): Clarify Pre Processing Stage

3.2 Convolution neural network phase:

After completing all pre-processing of the parking image, we use the proposed method CNN ResNet50 to evaluate the parking condition to determine if it is empty or occupied.

3.2.1 CNN layers:

CNN are sequential layers, each layer in this chain performs a specific function, the three types of layers are in order in the network:

**I- The Convolutional layer:** - This layer creates feature maps, which in turn show the unique features in the raw image. As the name implies, the work of the convolution layer is completely different from the work of other layers of the neural network, but rather contains filters that transform images to the feature map[11]. If the input image (I) and the kernel filter (K) are both of type 2D, the convoluted image is calculated as: [12]:

$$S(i, j) = \sum_m \sum_n I(m, n)k(i - m, j - n) \quad (2.4) [11]$$

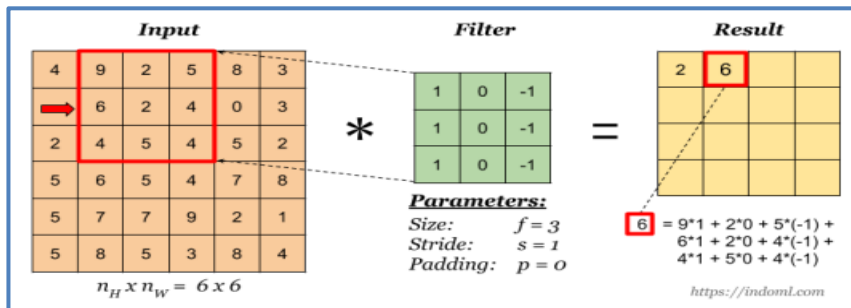
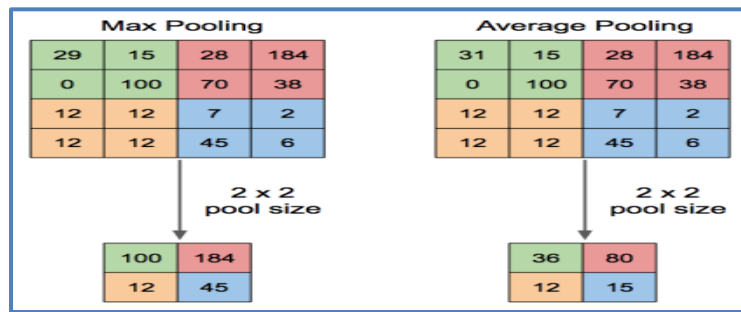


Figure 3: element-wise matrix multiplication in the convolutional layer [12]

**II - Pooling layer (subsampling layer):** - Dimensional reduction is performed immediately after the torsion process is completed. This results in a reduction of the parameter set, which in turn reduces both over-processing and training duration [13]. This layer plays a role in maintaining the input maps as well as the output maps as they are. As in [14] The formulation of this process is explained:

$$x_j^l = \text{down}(x_j^{l-1}) \quad (2.15) [13]$$



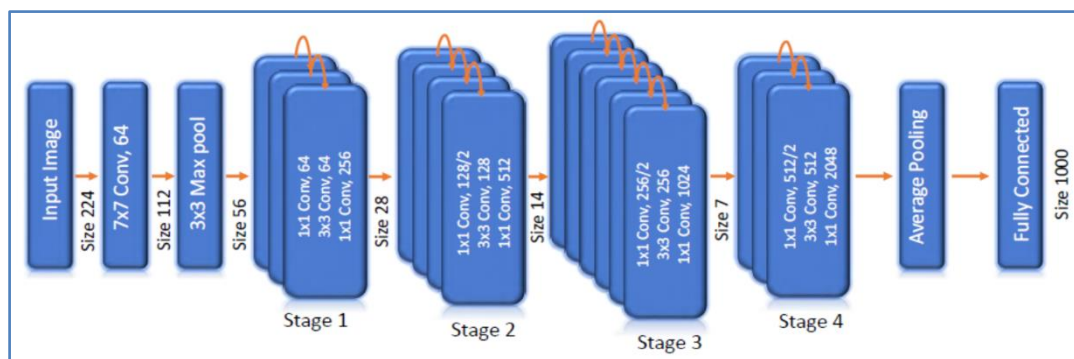
**Figure 4:** Shows two types of assembly [12].

**III -Fully connected layers:** - The income to the classification layer (fully connected network), obtained from the final output of the CNN layer [14], [15]. An entirely linked layer computes the outcome of each of the classes, Features extracted from the previous layer (the convolutional layer). The fully connected and forward neural layers are employed as the (soft-max). classification layer [14].

### 3.2.2 ResNet50

ResNet50 is the first deep CNN architecture to use residual learning increased accuracy in computer vision measurement challenges ResNet architecture [16] was the winning architecture for ILSVRC 2015 and consists of so-called ResNet blocks.

One of the challenges of deep CNNs and deep learning, in general, is the problem of gradient fading, where gradients during backpropagation become too small for shallow layers. To meet this challenge, the main innovation in this architecture is the presence of “skip connections” or identity mapping (orange curved lines on top of the blocks) as shown in Figure 5, where the output of the previous block is connected to the next block. This skipping connection helps alleviate the problem of gradient vanishing by skipping one or more layers. The result is a deep web with extremely precise image classification. The input to the grid is a 224 x 224-pixel image and the output is a 1000-dimensional theme vector. The ResNet-50 model consists of 5 stages, each with a convolution and matching block. Each wrap block has 3 wrapping layers and each matching block also has 3 wrapping layers. [16]



**Figure (5):** ResNet50 architecture[7]

### 3.2.3 Training of ResNet50

ResNet50 training is to find kernels in convolutional layers as well as weights in FC layers which in turn reduces the differences between output predictions and base truth labels in the training dataset (PKLot). The use of the backpropagation algorithm is the common way to train neural networks and the use of an adam-type



algorithm where the learning of each parameter is preserved, and the learnable parameters are updated, by adjusting the weights and parameters as shown in Table (1).

**Table (1):** Description of network parameters

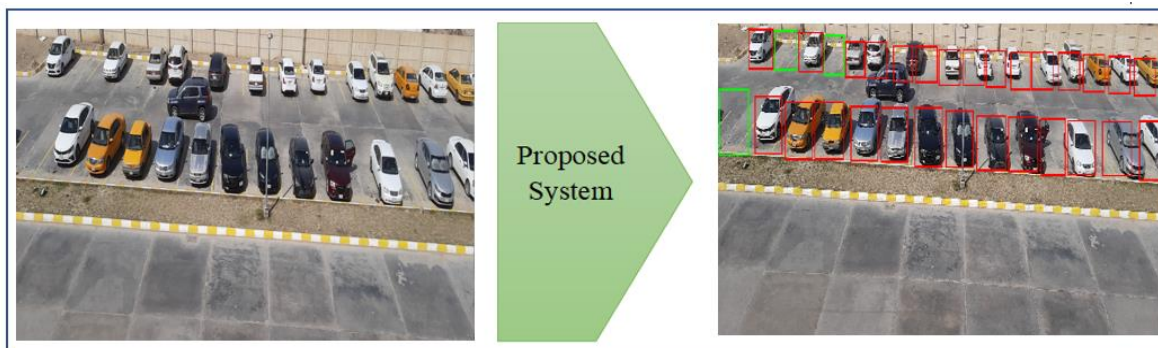
| Parameter Name   | Parameter Value |
|------------------|-----------------|
| Learning_rate    | 0.00001         |
| Max Epochs       | 2               |
| MiniBatchSize    | 8               |
| InitialLearnRate | 1e-4            |

### 3.2.4 Test of ResNet50

The testing process begins immediately after the end of the training. The 100 test samples from PKLOT data and 71 from local data were separated into 80% for training and 20% for testing on ResNet50 models that we trained previously.

### 3.3 The classification phase:

During the training phase, an image was taken from the parking monitoring camera, so that the parking lots are detected every 60 seconds. Then, the individual parking area is cropped according to the input coordinates and the image is resized to 224 x 224. After that the resulting image is entered into ResNet50, which will make a judgment on whether the individual parking lot is empty or occupied, by comparing it to the input image from the camera with rated test samples images. Figure (6) shows the classification of images through the detection system for parking spaces.



**Figure (6):** the classification of images through the detection system for parking spaces.

## 4. Experimental results

### 4.1 Datasets

#### 4.1.1 the PKLot dataset:

The PKLot dataset consists of 12,417 parking images and 695,899 segmented parking images that were precisely identified and manually tagged. All of these images were obtained in the parking lots of the Federal University of Paraná (UFPR) as well as the Pontifical University (PUCPR), both universities located in Paraná

(from the city of) Curitiba, in Brazil. Captured with an interval of every five minutes, the environment changes, for thirty days during the day in three kinds of weather, namely, sunny, rainy, and cloudy days. Users of HD cameras, low cost (Microsoft LifeCam, HD-5000) from the top of a building to reduce blockages between or behind adjacent vehicles. Pictures are taken from different directions and locations covering cars from more than one angle and in different sizes. The number of non-empty parking spaces at 48.54% and empty parking spaces at 51.46% represented approximately equal proportions from the entire PKLot data set [17].

#### 4.1.2 local database:

Image samples were obtained by the researcher for this study. The data set consists of 175 car park images and 5250 fragmented car park images, that were precisely identified and manually tagged. All these images were obtained in the parking lots of Nasiriyah General Hospital located in Dhi Qar Governorate/ Iraq.

It was acquired in a period of time according to the changing of the parking scene from 9:15 am to 5:00 pm for one day. Using a camera with a resolution of 64 megapixels from the top of a two-story building to reduce obstruction that may occur between neighboring vehicles or those behind them.



A- A sample of the PKLot dataset. [16]



B- A sample of the local database.

**Figure (7):** Sample of data set used by study

#### 4.2 Evaluation criteria

To evaluate the proposed system, we use a number of metrics: first, accuracy, second, Precision, third recall, and measure F, as defined in equations 1, 2, 3, and 4 [18]. The symbols in the equations mean that TP (true positive) is the number of sub-images classified as occupied and is actually occupied, TN (true negative) is the number of unoccupied sub-images classified as unoccupied, and FP (false positive) is the number of sub-images classified as occupied and not actually occupied. FN (False Negative) is the number of sub-images categorized as unoccupied and actually occupied.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F-score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (4)$$

#### 4.3 Implementation details

After completing the training, the test procedure begins. Whereas the CNN classifier used to test new unclassified images is the classifier created during the training process, parking image, then the parking image is listed as empty or occupied 80% of samples were selected during the training stage, at random for training ResNet50. The remaining 20% of images were randomly selected from all samples to perform the proposed CNN performance test. Also, benchmarks are calculated, at this point, by comparing the results with the actual images.

Based on MATLAB R2021a language ResNet50 was trained and tested with ease, implementing all CNN codes, in PC an MSI that has specifications such as Intel(R) Core (TM) i7- 10750H @ 2.60 GHz for CPU, windows11Home,16 GB of RAM, and 64-bit Operating System and GPU (RTX3060).

#### 4.4 Evaluation results

Through the proposed regime, we have achieved an accuracy of 99.67 % using 100 images from the PKLot dataset, which are in different weather conditions (sunny, rainy, and cloudy) and we achieved an accuracy of 99.12% using 71 images from the local database that are at different times of the day. Also, when transferring learning using a ResNet50 network trained on PKLot dataset on local database images that were not seen by the network, our proposed system achieved an accuracy of 98.18% and the average time taken to test the image is 0.5 sec. Table 2 presents the results of the main criteria for classifying the proposed model.

**Table 2:** Results of the proposed model classification criteria.

| <b>Evaluation criteria</b> | <b>PKLot dataset</b> | <b>local dataset</b> |
|----------------------------|----------------------|----------------------|
| <b>Accuracy</b>            | 99.67 %              | 99.12%               |
| <b>precision</b>           | 99.59 %              | 99.43 %              |
| <b>Recall</b>              | 100 %                | 99.43 %              |
| <b>F-measure</b>           | 99.79 %              | 99.43 %              |

#### 5 Compared with other models

This section presents a performance comparison with other parking detection systems. This comparison is based on parking detection systems using deep learning in terms of accuracy only because implementation time is similar. The detection accuracy of parking spaces in this study is higher than in others. Table No. (3) shows the results of the proposed system with others.

**Table (3):** Comparison of the results of the proposed system with other deep learning-based parking occupancy detection models.

| <b>References</b>                    | <b>Model</b>    | <b>Recognition Accuracy</b> |
|--------------------------------------|-----------------|-----------------------------|
| Wei Li et al. (2020) In [9]          | VPS-Net         | 99.63 %                     |
| Albertus Farley et al (2020) In [10] | mAlexNet        | 93.15 %                     |
| Acharya et al. (2018) In [7]         | VGGNet- SVM     | 99.60 %                     |
| <b>The Proposed System (2022)</b>    | <b>ResNet50</b> | <b>99.67 %</b>              |

#### 6. Potential for commercialisation

When The ResNet50 experiment, 71 samples (parking images) were used from the local dataset containing 2201 individual parking lots, 36 empty spaces were diagnosed as occupied by the error, and no vacant spaces were classified as Busy with a car, which means that the accuracy of the network performance on images that you



have not seen before, was 98.18% and the average time taken to test an image is a second and a half. This indicates the possibility of marketing the system because the system is ready for implementation in any street or outdoor parking lot in residential areas. Just enter the coordinates of the individual car parks for this parking lot without any training and it can start working directly from the moment of installation, and it will provide its services efficiently. The great potential of this system can be used as a commercial framework for a practical PGI system that provides a high degree of accuracy and is cheaper than sensor-based systems.

## 7. Conclusion

An image-based framework is developed in this paper to determine parking space occupancy in the outdoor environment using a pre-trained deep CNN. The framework achieved a high accuracy of 99.67 % on the public training dataset (PKLot dataset), and an accuracy of 99.12 % on the independent test dataset created by the researcher, indicating its suitability for applications where the framework can provide a cheap and reliable solution to PGI systems in external environments. However, there are some performance-limiting challenges in transfer learning including, parking outside or between the area designated by drivers and biasing the training data used.

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