smart cities

*Review*

# A Review of Parking Slot Types and their Detection Techniques for Smart Cities

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**Abstract:** Smart parking system plays a critical role in the overall development of the cities. The capability to precisely detect an open parking space nearby is necessary for autonomous vehicle parking for smart cities. Finding parking spaces is a big issue in big cities. Many of the existing parking guidance systems use fixed IoT sensors or cameras that are unable to offer information from the perspective of the driver. Accurately locating parking spaces can be difficult since they come in a range of sizes and colors that are blocked by objects that seem different depending on the environmental lighting. There are numerous auto industry players engaged in the advanced testing of driverless cars. A vacant parking space must be found, and the car must be directed to park there in order for the operation to succeed. The machine learning-based algorithms created to locate parking spaces and techniques and methods utilizing dashcams and fish-eye cameras are reviewed in this study. In response to the increase in dashcams, neural network-based techniques are created for identifying open parking spaces in dashcam videos. The paper proposed the review of the existing parking slot types and their detection techniques. The review will highlight the importance and scope of a smart parking system for smart cities.

**Keywords:** smart cities; smart parking; machine learning; dashcams; shuttle parking system; fish-eye; YOLOv2; IoT

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## 1. Introduction

The administration of parking lots in smart cities effectively depends heavily on methods for detecting occupancy in parking spaces. Reducing lines, enhancing scalability, and decreasing the time needed to locate an empty spot in a parking lot can all be achieved with the use of real-time parking space availability information and user communication [1]. One of the main reasons parking lot collisions occur is driver distraction brought on by looking for a parking spot, as people are frequently too preoccupied to look out for moving traffic or pedestrians. When the parking lot is crowded with cars and pedestrians, the situation is hazardous. By promptly providing drivers accurate information about the availability of parking spaces, an intelligent parking guidance system can reduce some of this hassle [2]. In the era of self-driving cars, the vehicle should be capable of searching for parking spots on its own, and parking slot identification should then work to locate a parking slot precisely [3]. Utilizing machine learning models to identify parking spaces is not only necessary for autonomous vehicles, but also benefits humans by lowering accident risks, increasing parking space utilization, speeding up vehicle parking, and providing a host of other advantages. In order to identify a parking space, numerous techniques have been developed, both visual and non-visual (sensor based). Researchers use a variety of cameras to photograph parking spaces and part of these strategies are monocular, binocular, RGB-D, fish-eye, dashcam, etc. [4].

Utilizing an automated and organized parking system may reduce the amount of labor required from people while allowing it to run efficiently and avoid delays. Around-view monitor (AVM) systems are present in automobiles to aid drivers in keeping an eye on the surrounding road conditions. Using the vehicle's built-in cameras, it is extremely useful to identify parking spaces on around-view images [5]. Due to alterations in illumination, shadows, and occlusion, using eyesight to find parking spaces is still quite difficult. The authors [6] analyzed vision-based parking slot detection for the first time. Based on the fact that the parking space markings are a consistent, background-distinct color in the picture [6]. The values of the technique are easily impacted, so in various lighting conditions, digital images will significantly vary. There are three different types of parking and are discussed in the below sub-section:

### *1.1. Parallel Parking*

Vehicles are parked parallel to the road or walkway in a parallel parking arrangement. In parallel parking, an automobile is parked on the same side of the road as other parked cars while facing the same direction as the flow of traffic on that side of the road. Figure 1 shows the representation of parallel parking.

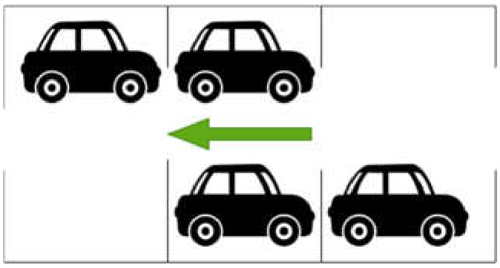


**Figure 1.** Parallel parking representation.

To accomplish this, one must first approach the parked car from behind and pull up next to it. Then, one must gradually reverse to fit into the area while maintaining a safe distance. One should not simply put their car in the first available place when parallel parking. To determine whether your car will fit in the allocated parking place, careful examination is required [7]. As a general guideline, the parking spot needs to be 1.5 times as long as your vehicle. If a suitable spot does not appear right away, keep looking. Once the ideal location has been found, the vehicle should be parallel parked behind another vehicle. A distance of 2–3 feet should be maintained between you and the object [7]. Then, the automobile should be slowly reversed until the center of your automobile is parallel to the rear bumper of the opposing vehicle. Your car will now begin to turn so as to pass the vehicle in front of it. Here, keeping a safe distance from the other car will pay off because you will have enough room to reverse without running the risk of hitting the other car. Once the steering wheel is at a 45° angle to the right, it shifts into reverse and keeps going. When your automobile is parallel to the wall or divider on the driver's side and perfectly positioned with the other vehicles, turn the steering wheel counterclockwise and keep reversing [7]. The last step is to make sure your car is traveling at an equal distance from the vehicles in front of and behind it, as well as from the edge of the road. If not, move your car until it is in the middle and displays perfectly parallel lines [7].

### *1.2. Perpendicular Parking*

Unlike parallel parking, which expects vehicles to align parallel to the aisle or curb, perpendicular parking requires vehicles to be positioned side-by-side perpendicular to the aisle or curb. It is a type of angled parking that is frequently employed when parking spots need to be utilized effectively. The cars are typically driven straight ahead, or reverse parked into a spot, with the vehicles parked at a 90° angle to the curb [8]. The representation of perpendicular parking is shown in Figure 2.

**Figure 2.** Perpendicular parking representation.

### *1.3. Angled Parking*

Angled parking stresses economy of mobility and is frequently used in high traffic areas. This includes parking lots of supermarkets, theatres, retail center, and more. Choosing a good space is important in perpendicular parking. Before parking, it is frequently a good idea to take it easy and look for any open spots. It will be far more difficult to park in a position in the corner of a lot or that is entirely surrounded by cars on all sides [8]. Therefore, spots on the left side should be picked more habitually than those on the right as a general rule. Indicators should be turned on so the car behind knows that the car is turning. Angling into the location should be avoided; instead, it should be approached from a 90° angle. The wheel should be turned only until side mirror has passed through the center of the available spot prior to the one selected. Before returning the steering wheel to its middle position, it should be made sure that vehicle has fully backed into the parking space. The vehicle should be turned so that it is parallel to the other vehicles in the row and at a 90° angle to the curb. Mirrors should be used to make sure the vehicle is angled appropriately [8]. When angled parking is compared to parallel or perpendicular parking, it can accommodate more vehicles, and drivers do not have to make sharp bends to park their cars. Angled parking spaces have slots that slant at 60° and 45°, respectively. The slightly tilted parking place in the 60° parking lot model demands a turn of roughly 60° [9]. The representation of angled parking is shown in Figure 3.

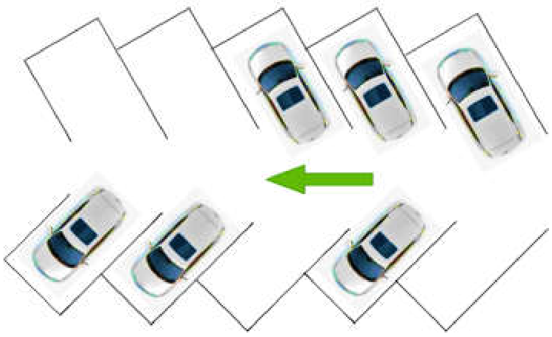


**Figure 3.** Angled parking representation.

It is a middle ground between straight and 45° parking spaces. The chance of an accident is also decreased as long as vehicles stay within the boundaries of their parking spaces. The likelihood of collisions and traffic jams is significantly reduced when everyone is travelling in the same direction, as this requires one-way traffic, which is safer than two-way traffic. Vehicles travel in a single lane as they wait to effortlessly pull into an angled position to their left or right. Drivers only have to worry about one way of traffic when leaving the area [9].

## 2. Related Work

In this section, the authors present a review of the literature that was performed on the parking detection system. Several types, techniques, and methods available in the literature are discussed.

The authors, Do, H., and Choi, J. Y. [10], proposed a context-based parking slot identification technique that was motivated by how a human driver locates a parking space. This technique uses two deep network modules, i.e., the parking context recognizer and the parking space detector. The authors also suggested new assessment criteria for parking slot identification, which reflects whether a car can fit in the discovered parking space. For which, they used Fish-Eye Image Dataset. Using MobileNetV2, VGG-16, and Resnet-50, the classification accuracy was 98%, while the orientation error ranged from 1.3 to 4.1 degrees.

Amato et al. [11] performed a parking space detection using mAlexNet and mLeNet, and subsequently trained SVM with RBF kernel to classify the parking. A technique that uses a convolutional neural network (CNN) classifier running on a smart camera with finite resources to determine the occupancy of parking spaces in real time. According to studies, this technique is quite accurate and robust against changes in lighting, the presence of shadows, and partial occlusions. By simultaneously watching around 50 parking spaces, one camera can cover a sizable area of a parking lot. MAlexNet outperformed mLeNet in performance. Accuracy of 82.90% on CNRPark and 90.40% on PKLot were attained. Chen et al. [12] suggested an extendable process called FakePS to help with the training of parking slot identification models using artificial data. One can construct numerous simulated parking settings with FakePS and then automatically gather labelled surround-view photos. It is recommended to use a pipeline called FakePS to improve parking slot identification models' performance in new scenarios that are not part of the actual training set. This pipeline makes it possible to gather lots of artificial surround-view photos from unity scenarios. Using the unlabeled real photos as a starting point, the proposed parking slot constancy loss refines the synthetic images while maintaining the parking spaces.

Zhang et al. [13] suggested an innovative solution to parking space recognition using deep convolutional neural networks (DCNN). The surround-view image is the input for the program called DeepPS. The two key operations in DeepPS are locating all the marking locations on the input image and identifying the local image patterns produced by paired marking problems. In order to make it easier to examine vision-based parking slot recognition, a sizable, labeled dataset is created. The largest dataset in this area consists of 12,165 surround-view photos taken at regular indoor and outdoor parking lots. The labeling of the parking spaces and marking points is conducted for each image. Datasets gathered have been used to confirm the effectiveness and efficiency of DeepPS. The recall rate for the full test set was 98.89%, while its precision rate was 99.54%. DeepPS is also suitable for time-sensitive self-parking systems because it can process one frame in 23 ms. Convolutional neural networks were suggested as a detector by Yu. Et al. [14] in order to boost speed and cut model size without sacrificing accuracy. To achieve the perfect balance, a system was developed to automatically choose the best receptive fields and prune the unnecessary channels after each training session. The proposed model can simultaneously recognize parking spot corners and line characteristics and works well in real time on common processors. The parking slot corner localization error of the model is 1.51–2.14 cm (std. err.), and the slot recognition accuracy is 98% at a frame rate of roughly 30 FPS on a 2.3 GHz CPU core.

The authors Huang et al. [15] proposed a DMPR-PS, or directional marking point regression. This is a parking slot detecting technique. The DMPR-PS is based on a novel CNN-based model designed exclusively for directional marking point regression. The model predicts the position, form, and orientation of each marking point on an image that is a surround view. With the use of geometrical laws, marking points and parking spaces could be simply deduced. With a precision rate of 99.42% and a recall rate of 99.37%, DMPR-PS surpasses cutting-edge rivals on the benchmark dataset. An end-to-end deep neural network that has been trained to automatically find and categorize parking spaces in surround-view pictures was proposed by the authors Zinelli, A., Musto, and Pizzati [16]. Four different cameras mounted on a truck provided diverse perspectives that were combined to create the image. The Faster R-CNN baseline forms the foundation of the network design. Because parking spaces can be seen from a variety of angles and with a variety of shapes, the anticipated bounding boxes are generic quadrilaterals rather than image-aligned rectangles. A modest training set of a few hundred hand annotated photographs has been created in order to train the network. The main advantage of this method over the state-of-the-art for parking slot detection is its capacity to accurately and generally detect a wide range of parking slot types, including parallel, perpendicular, and slanted slots, under diverse lighting and viewing conditions.

The authors, Xu, C., and Hu, X. [17] suggested the algorithm that directly detects parking spaces in the fish-eye image taken by the four-way fish-eye camera mounted on the car body. It makes use of an updated YoloV3 network structure. According to the experimental findings, the method's recall ratio on the custom parking dataset is 98.72%, and its accuracy is 99.14%. This algorithm was used to find a solution for the automatic parking system vision-based parking spot recognition issue.

The authors Suhr, J. K., and Jung, H. G. [18] suggested an approach for images from around view monitors (AVM) a one-stage trainable end-to-end parking space recognition. The suggested approach makes use of a convolutional neural network (CNN) to simultaneously gather global information (entry, type, and occupancy of parking slot) and local information (location and orientation of junction) and integrates them to detect parking slots with their characteristics. Using a grid to divide up an AVM image, this method uses CNN to extract features. The global and local information of the parking space for each grid cell is produced by convolution filters when applied to the recovered feature map. By integrating local and global parking space data using non-maximum suppression (NMS), final detection results are produced. A fully convolutional network without a region proposal step was used to gather the majority of the parking slot information used in the end-to-end trainable one-stage detector that is offered as the solution. In a quantitative test utilizing the public dataset, this method outperforms prior ones with a recall and precision of 99.77%, a type with classification accuracy of 100%, and an occupancy classification accuracy of 99.31% while processing 60 frames per second.

The authors, Yan Wu et al. [19], developed a segmentation approach for parking slot and lane markers based on the PSV dataset using a highly fused convolutional network (HFCN). Four calibrated images from four fish-eye cameras were combined to provide a surround-view image. The authors collected and annotated more than 4200 surround-view photos, which include a variety of illuminated scenes of various parking spaces. A VH-HFCN network is suggested, which uses an HFCN as the base with a more effective VH stage to separate different markers more effectively. Two separate linear convolution routes with vertical and horizontal convolution kernels make up the VH-stage. Using the object identification framework of deep learning, the authors, Deepak Poddar et al. [20], proposed an efficient approach for instantiating parking places at the pixel level. The updated Single Shot Detector object detection meta-architecture and MobileNet-V1 network architecture, which served as the foundation for the convolutional neural network, were used in the method to execute parking space instantiation directly in the fish-eye domain. The principal key-points of parking spaces have been inventively added to the traditional SSD meta-architecture of object detecting functionality in order to precisely define parking spot boundaries. The suggested approach achieves accuracy of 0.76 OKS in four corner points per detection and 0.87 mAP for detected rectangular boxes enclosing parking spaces.

The authors, Zhang, C., and Du, B. [21], proposed a parking spot recognition algorithm based on pictures taken by already installed security cameras at parking lots. Locating a parking spot, the identification of parking lines, and the extraction of vehicle features all include the usage of photographs. The problem of vehicle occlusion brought on by the low installation height of security cameras in parking lots is addressed. To provide drivers with crucial information about the condition of parking spots, the suggested detection approach could classify vacant and occupied parking spaces. To verify the viability and correctness of the suggested approach, a number of tests were carried out in diverse environmental settings. Even in the presence of the car occlusion effect, imperfect parking lines, and different interferences, the positive experimental findings demonstrated the resilience and effectiveness of the suggested detection approach. Under diverse environmental circumstances, satisfactory detection success rates have been demonstrated. Zhihua Chen et al. [22] proposed a multi clue recovery model-based approach for reconstructing parking places called the Generative Parking Spot Detection. In the suggested method, the parking space is first geometrically disassembled to designate the locations of its corresponding corners. The next step is to locate corners from a ground image taken by a car's camera using a micro target recognition network. In order to appropriately recover a trustworthy true parking location, the fully pairing map was corrected using the multi clue model after these steps. The experimental findings showed that the recommended method outperformed a number of other current algorithms in terms of accuracy, which may reach more than 80% in most test circumstances.

The authors, Athira A. et al. [23], had provided a comparison of the different methods for locating parking spaces. As an alternative to sensor-based systems, image processing-based system models have been proposed. The study had presented an optical character recognition-based method for parking space identification that is both very effective and straightforward. The camera that has been installed in the parking lot captures an image of the area with the specifically numbered parking slots. In order to identify unoccupied spaces, the optical character recognition system recognizes the numbers that are not obscured by a car parked over them. Giulio Bacchiani et al. [24] suggested a technique that applies the Progressive Probabilistic Hough Transform on the space created by the fish-eye picture point projection onto the equivalence sphere. In contrast to traditional bird's-eye view-based methods, the technology allowed for long-range precision and the ability to pinpoint road marking segments immediately on the fish-eye image. To test the viability of a system, a straightforward parking space detector based on recognized road markings was created.

The authors Kazukuni Hamada et al. [25] developed a parking lot detecting method based on surround view. When parking vacancies were discovered and then started to disappear from the surrounding view, a useful tracking algorithm was presented to address the situation. A tracking approach was used to resolve a detection failure involving parking spaces that vanished from the surrounding view.

Jung et al. [26] developed a parking detecting technique that allowed the driver to select two parking lot line entrance positions. This strategy lowered computing costs and increased detection accuracy. Even though the method had a high degree of accuracy (over 90%), it was ineffective when there was noise during white line identification, there was sunlight, or the driver was operating a touch panel. In order to provide an end-to-end training model for parking slot detection in automatic parking systems (APSs), De-Hui Jian and Chang-Hong Lin [27] presented a line semantic segmentation model and a point semantic segmentation model based on multi-task learning that were linked. In the post-processing stage, the coordinates of the real parking spaces were found using the proposed models, which also produced images of the entrance line and corner center points. The model achieved an f-measure of 96.06% and a precision of 99.40%.

In order to recognize objects in images, the authors, Wei Liu et al. [28], suggested using single deep neural network method. A key element of the model is the use of multi scale convolutional bounding box outputs connected to several feature maps at the top of the network. The network creates modifications to the default boxes to better fit the shape of the objects and scores the presence of each object category in each box at prediction time. The network combines predictions from several feature maps with various resolutions to naturally handle objects of various sizes. According to experimental results on the PASCAL VOC, COCO, and ILSVRC datasets, SSD is substantially faster, providing a unified framework for both training and inference, and has competitive accuracy with methods that also contain an additional item proposal phase. SSD outperforms a comparable state-of-the-art Faster R-CNN model on the VOC2007 test at 59 frames per second using an Nvidia Titan X, scoring 74.3% mAP for 300,300 input and 76.9% mAP for 512,512 inputs.

The authors, Andrew G. Howard et al. [29], proposed a group of effective models known as MobileNets for using in embedded and mobile vision applications. It has been suggested to use two simple, global hyperparameters to efficiently balance latency and accuracy. These hyperparameters allow the model builder to choose the right sized model for their application based on the constraints of the problem. YOLO, an integrated object detection model, was suggested by Joseph Redmon et al. [30]. The model may be trained on entire images and is simple to construct. In contrast to classifier-based approaches, the entire model is trained concurrently, and YOLO is trained on a loss function that is directly related to detection performance. The YOLO model performs real-time image processing at a rate of 45 frames per second. Despite processing only 155 frames per second, Fast YOLO, a scaled-down version of the network, outperforms other real-time detectors in mAP by a ratio of two. In contrast to YOLO, modern detection techniques produce less false positive predictions on the background. Finally, YOLO picks up very broad representations of various objects.

The feature maps from all earlier layers are used as inputs for each layer, and the feature maps specific to each layer are used as inputs for all subsequent layers. The suggested model assessed the architecture on four very competitive benchmark tasks for object recognition (CIFAR-10, CIFAR-100, SVHN, and ImageNet). On the majority of tasks, DenseNets outperform the state-of-the-art while using less processing resources to achieve same performance. A real-time object detection system is proposed by the authors Robert J. Wang, Xiang Li, and Charles X. Ling [31] by combining PeleeNet with the Single Shot MultiBox Detector (SSD) approach and speeding up the architecture. Our proposed detection system1, called Pelee, achieves 76.4% mAP (mean average precision) on the PASCAL VOC2007 dataset and the MS COCO dataset at a speed of 23.6 frames per second on the iPhone 8 and 125 frames per second on the NVIDIA TX2. In terms of higher precision, with 13.6 times lower computational cost, and 11.3 times smaller model size, the COCO result performs better than YOLOv2.

## 3. Techniques of Parking Detection

### *3.1. Sensor-Based Techniques*

Sensors play a crucial role in parking slot detection by providing real-time information about the availability of parking spots. In parking system applications, a variety of sensors are used.

#### 3.1.1. Ultrasonic Sensors

To identify the presence of automobiles in parking places, they are frequently utilized in parking detection systems. When a vehicle passes over these sensors, high-frequency sound waves are emitted, which bounce back to the sensor. The sensor can calculate how far a vehicle is from it by timing how long it takes for the sound waves to return. In a parking detection system, ultrasonic sensors are usually installed on the ceiling or walls of the parking garage [32]. The parking control system receives a signal from the ultrasonic sensor when a car pulls into a parking spot. The parking control system then updates its database to indicate that the parking space is occupied. Ultrasonic sensors are inexpensive and easy to install. These sensors are affected by weather conditions and other sources of noise, which can cause false readings. To reduce the likelihood of false readings, ultrasonic sensors are often used in conjunction with other sensors, including magnetic sensors or cameras, to provide redundant detection [33].

#### 3.1.2. Infrared Sensors

They can detect the presence of vehicles regardless of the lighting conditions. They work by emitting infrared radiation and detecting the reflection of this radiation from a vehicle. Infrared sensors consist of an emitter, which emits infrared radiation, and a receiver, which detects the reflection of this radiation [34]. When a vehicle enters the field of view of the sensor, the infrared radiation emitted by the sensor is reflected by the vehicle and detected by the receiver. The distance between the sensor and the vehicle can be calculated based on the time it takes for the infrared radiation to travel to the vehicle and back to the sensor. This data is used to assess if a parking place is occupied or not. Infrared sensors are particularly useful in outdoor parking lots, where lighting conditions can vary significantly throughout the day [35].

#### 3.1.3. Magnetic Sensor

It operates by spotting modifications in the magnetic field brought on by the presence of a vehicle. It consists of a magnetic field generator and a detector. A magnetic field is produced in the parking area by the magnetic field generator, and the presence of a vehicle causes changes in the magnetic field, which are picked up by the detector [36]. When a vehicle enters a parking space, it creates a disturbance in the magnetic field, which is detected by the detector. The magnetic sensor can determine whether a parking space is occupied or not based on the strength and duration of the disturbance in the magnetic field. A central control system that can offer real-time information on parking space occupancy can receive this information and deliver it to the appropriate parking spaces [37]. Magnetic sensors are typically embedded in the pavement of parking spaces and are relatively easy to install.

#### 3.1.4. Inductive Loop Detector Sensors

They are placed in the ground and work by detecting changes in the magnetic field caused by the presence of a vehicle. The sensors consist of a loop of wire embedded in the ground. The loop is associated with a control system that recognizes modifications in the magnetic field brought on by the presence of a car. The loop senses the disruption in the magnetic field caused when a car pulls into a parking spot [38]. The control unit can determine whether a parking space is occupied or not based on the strength and duration of the disturbance in the magnetic field. A central control system that can offer real-time information on parking space occupancy can receive this information and deliver it to the appropriate parking spaces. These sensors are highly accurate and can detect the presence of a vehicle with a high degree of precision. They are also relatively easy to install and can be integrated with other types of sensors for enhanced accuracy and functionality [39].

#### 3.1.5. Light Detection and Ranging (LiDAR)

It uses laser beams to measure the distance between the sensor and the target object, creating a 3D map of the surrounding environment. LiDAR is used to monitor the movement of vehicles in and out of parking spots [40]. This information is used to optimize parking lot usage, reduce congestion, and improve overall traffic flow. LiDAR-based parking detection systems also provide real-time data on parking availability, which can be used to guide drivers to available spots and help reduce the time spent circling the lot in search of a parking space [41].

#### 3.1.6. Microwave Radio Detection and Ranging (Radar)

It uses radio waves to identify and find objects. Radar sensors emit a radio signal that travels through the air and reflects off of objects, including vehicles. The radar sensor then detects the reflected signal and uses the information to determine the distance and location of the vehicle [42]. A central system can receive this data to track parking availability and direct drivers to open spots. This detects multiple objects at once, making them ideal for use in crowded parking lots [43].

#### 3.1.7. Radio Frequency Identification (RFID)

It is a technology that recognizes and tracks objects using radio waves. RFID sensors can be used to detect the presence or absence of automobiles in parking places in the context of parking detection. RFID sensors work by emitting a radio signal that is picked up by an RFID tag attached to the vehicle [44]. The RFID tag contains a unique identification number that is transmitted back to the sensor. The sensor then uses this information to determine whether the parking space is occupied or not. One advantage of RFID sensors is that they are relatively low cost and easy to install [45].

#### 3.1.8. Anisotropic Magneto Resistance (AMR) Sensors

These sensors are commonly used for detecting changes in magnetic fields. The basic principle behind AMR sensors is that they have a varying electrical resistance based on the direction of the magnetic field passing through them. This makes them ideal for detecting the presence of a nearby metallic object. AMR sensors can be placed at regular intervals in a parking slot and connected to a central control unit [46]. When a vehicle pulls into a parking spot, the metal in the vehicle disturbs the magnetic field surrounding the sensor, changing its electrical resistance. This change is detected by the control unit, which then registers the presence of a vehicle in the corresponding parking space. One of the advantages of using AMR sensors for parking detection is their high sensitivity to magnetic fields. This allows them to detect the presence of a vehicle even at low speeds or from a distance. It is inexpensive and easy to install [47].

#### 3.1.9. Piezoelectric Sensors

These are commonly used for parking slot detection due to their high sensitivity to pressure changes. When a vehicle drives over a piezoelectric sensor, the weight of the vehicle causes the sensor to generate an electrical signal that can be used to detect the presence of a vehicle in a parking slot [48].

#### 3.1.10. Microwave Radar Sensor

It is a type of parking detection sensor that uses radio waves to detect the presence of vehicles in a parking space. The sensor emits a low-power radio signal and measures the reflection of the signal off of nearby objects, including vehicles. The radio waves are reflected back to the sensor when a vehicle pulls into a parking spot, and the sensor recognizes the vehicle presence and transmits a signal to a parking management system [49]. Microwave radar sensors can be installed above or below ground and are highly accurate, even in adverse weather conditions. Microwave radar sensors are commonly used in parking garages and outdoor parking lots because they are able to detect vehicles regardless of their size or material, such as metal or plastic. They are also able to detect multiple vehicles in a single parking space and can be used to monitor the occupancy of entire parking lots or garages [50].

### *3.2. Position-Based Techniques*

#### 3.2.1. Surface-Mounted Sensors

These are installed on the surface of the parking space and are used to detect the presence of a vehicle parked above it. They are often used in indoor parking garages and can be easily installed without requiring any excavation or drilling.

#### 3.2.2. Buried Sensors

They are positioned underneath the parking space's surface and look for vehicles. They are frequently utilized for outdoor parking.

#### 3.2.3. Wireless Sensor

It uses wireless technology to transmit data about parking availability to a central system. These sensors can be surface-mounted or buried and can be easily installed without requiring any wiring or cabling.

#### 3.2.4. Multi-Level Sensors

They are used in multi-level parking garages to monitor parking availability in real time and to monitor the presence of vehicles on each level. They can be surface-mounted or buried and are often connected to a central system that displays parking availability to drivers.

There are several advantages of sensor-based parking detection:

- Accuracy: sensor-based systems can determine whether a vehicle is present or not with greater precision and reliability, and this is particularly important in low-light or adverse weather conditions.
- Consistency: sensor-based systems provide consistent results, regardless of lighting conditions or other external factors, and this makes them more reliable and predictable, and less prone to errors or false positives.
- Lower cost: sensor-based systems are generally less expensive, as they require fewer components and are easier to install and maintain.
- Integration with other technologies: other smart city technologies, such traffic management systems, can be easily integrated with sensor-based systems, to provide a more comprehensive and efficient solution for parking and transportation management.

### *3.3. Vision-Based Techniques*

In this category, a combination of machine learning algorithms and computer vision techniques to detect parking spaces is used, which can be marked with lines or other indicators. The algorithm can analyze the images captured by the cameras and identify parking spaces and their availability. In order to extract patterns and characteristics from massive volumes of data, deep learning approaches employ artificial neural networks with several layers [51]. Deep learning algorithms can be used to automatically learn and detect parking slots in photos or videos in the context of parking slot detection. There are different approaches for vision-based parking detection.

#### 3.3.1. Object Detection Based

It is a popular category of vision-based parking detection techniques. Some commonly used object detection-based approaches for parking detection are given below:

- YOLO (You Only Look Once) is a popular object detection algorithm that can detect objects in real time by dividing the image into a grid of cells and predicting the class and location of the object in each cell. YOLO can detect multiple objects in an image and has been applied to parking detection tasks with high accuracy and speed [52].
- SSD (Single Shot Detector) is a single-shot object identification system that uses several convolutional feature maps of various scales to predict the kind and location of objects. SSD can detect objects of different sizes and aspect ratios and has been applied to parking detection tasks with high accuracy and efficiency [53].
- Faster R-CNN is a state-of-the-art object detection algorithm that uses a region proposal network (RPN) to generate object proposals and a convolutional neural network (CNN) to classify the proposals and refine their bounding boxes. Faster R-CNN has shown promising results in detecting cars in parking lots, and it can handle different parking lot layouts, lighting conditions, and car orientations [54].
- RetinaNet is a recent object detection algorithm that uses a novel focal loss function to address the class imbalance problem in object detection tasks. RetinaNet can detect objects with high precision and recall and has been applied to parking detection tasks with promising results [55].
- Mask R-CNN is a variant of Faster R-CNN that can also predict object masks in addition to bounding boxes and class labels. Mask R-CNN has been applied to parking detection tasks to segment and track cars in parking lots [56]. To identify the presence of automobiles in parking places, they are frequently utilized in parking detection systems.

#### 3.3.2. Background Subtraction Based

These approaches use the difference between the current image and the background image to detect moving objects. Some frequently used background subtraction-based approaches for parking detection are as follows:

- Gaussian Mixture Model (GMM) is a widely used background subtraction algorithm that models the pixel intensities of the background as a mixture of Gaussian distributions. GMM can adapt to changes in the scene and can detect moving objects in real time. GMM has been applied to parking detection tasks to detect cars in parking lots and estimate parking space occupancy [57].
- Adaptive background subtraction methods update the background model continuously based on the current image and the previous background model. This method can handle gradual changes in the scene and can detect moving objects in real time. Adaptive background subtraction methods have been applied to parking detection tasks to detect cars in parking lots and estimate parking space occupancy [58].
- ViBe is a background subtraction algorithm that uses a pixel-based sampling strategy to detect moving objects in the scene. ViBe can learn the background model from a few frames and can detect objects with low computational cost. ViBe has been applied to parking detection tasks with promising results [59].

#### 3.3.3. Feature Based

These approaches extract features from the image, such as edges, corners, and texture, and use these features to detect parking spaces and estimate occupancy. Some commonly used feature-based approaches for parking detection are as follows:

- Hough Transform is a feature-based approach that detects straight lines in the image. In parking detection tasks, Hough Transform can be used to detect the edges of parking spaces and estimate their orientation and position. Hough Transform can also be combined with other techniques such as color segmentation and contour detection to improve its accuracy and robustness [60].
- Haar-like features are rectangular features that can be used to detect edges and corners in the image. Haar-like features have been applied to parking detection tasks to detect parking spaces and estimate their occupancy. Haar-like features can also be combined with machine learning techniques such as AdaBoost and SVM to improve their accuracy and efficiency [61].
- Local Binary Patterns (LBP) is a texture-based feature extraction method that can detect local patterns in the image. LBP can be used to detect the texture of parking spaces and estimate their occupancy. LBP can be combined with other techniques such as edge detection and clustering to improve its accuracy and robustness [62].
- Scale-Invariant Feature Transform (SIFT) is a feature extraction technique that can find and match important image points. SIFT can be used to detect the corners and edges of parking spaces and estimate their occupancy. SIFT can be combined with other techniques such as contour detection and clustering to improve its accuracy and robustness [63].

#### 3.3.4. Deep Learning Based

These approaches for parking detection involve training a neural network model to detect parking spaces and estimate their occupancy. These approaches typically involve using convolutional neural networks (CNN) to extract features from the input image and make predictions about the occupancy of parking spaces. Some commonly used deep learning-based approaches for parking detection are as follow:

- Deep convolutional neural networks (DCNNs) are a type of neural network that can be used for parking detection tasks. DCNNs use multiple layers of convolutional filters to extract features from the input image and predict the occupancy of parking

spaces. DCNNs can be trained on large datasets of parking lot images to improve their accuracy and robustness [64].
- Transfer learning is a technique that involves a pre-trained neural network model for parking detection tasks. Transfer learning can be used to leverage the knowledge learned by the pre-trained model on large datasets of images and apply it to parking detection tasks. Transfer learning can be used with various neural network models including VGGNet, ResNet, and InceptionNet [65].

These deep learning-based approaches can be combined with other techniques including data augmentation, object tracking, and clustering to improve their accuracy and robustness for parking detection tasks. The advantages of vision-based parking detection are as follows:

- More detailed information: Vision-based systems can provide more detailed information about the parking environment, such as the type of vehicle, its orientation, and its license plate number. This information can be valuable for parking management and enforcement purposes.
- Greater flexibility: Vision-based systems can be more flexible and adaptable to changing environments or different parking scenarios. For example, they can detect multiple vehicles in the same parking space or detect vehicles parked in non-designated areas.
- More accurate in certain scenarios: vision-based systems can be more accurate in certain scenarios, such as detecting vehicles parked partially outside of a designated parking space or detecting motorcycles or bicycles.
- Higher resolution: vision-based systems can provide higher resolution images or video feeds, which can be used for additional applications, such as security or surveillance.
- Easy installation: Vision-based systems require minimal physical installation, as they can be mounted on existing infrastructure or deployed using mobile units. This can make them more cost-effective and easier to install than sensor-based systems.

There are several advantages of vision-based parking detection:

- Visual data input: image-based parking systems rely on visual data captured by cameras or dashcams installed in parking areas.
- Machine learning algorithms: these systems often employ machine learning algorithms, such as convolutional neural networks (CNNs), for object detection and recognition.
- Dataset requirements: training image-based parking systems typically require large and diverse datasets of parking scenarios to achieve accurate results.
- Real-time processing: some image-based systems are capable of real-time image analysis to detect parking space availability.
- Object detection: they are effective at detecting various objects in parking lots, including vehicles, pedestrians, and obstacles.
- High-resolution images: image-based systems can provide high-resolution images, allowing for detailed analysis of parking spaces and their surroundings.
- Detailed information: These systems can offer detailed information about the parking environment, including vehicle type, orientation, and even license plate recognition.
- Flexibility: they can adapt to changing environments, handle multiple vehicles in the same space, and detect vehicles parked outside designated areas.
- Accuracy: image-based systems can be highly accurate in various scenarios, including detecting vehicles partially outside designated spaces or identifying smaller vehicles like motorcycles and bicycles.
- Ease of installation: they require minimal physical installation, often using existing infrastructure or mobile units.

## 4. Parking Datasets

The different available datasets for parking detection system are shown in Figure 4.

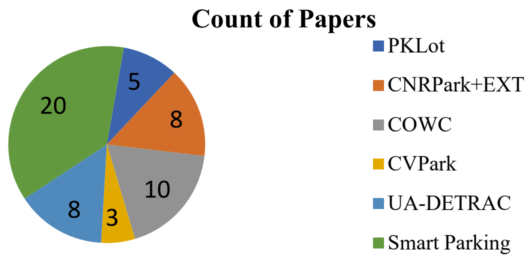
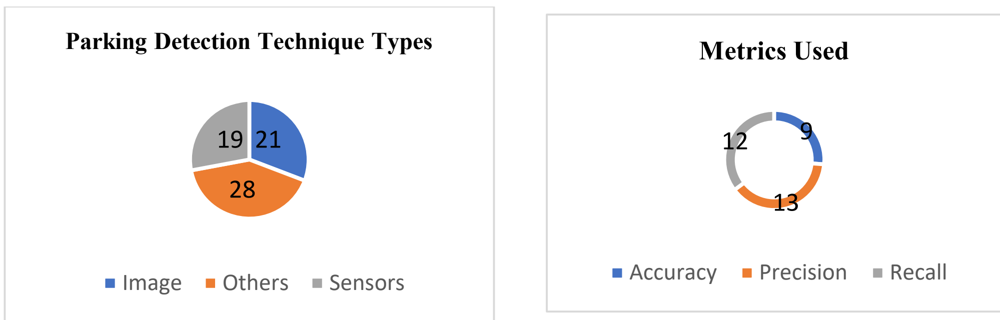



**Figure 4.** Count of papers for different available datasets.

The different datasets included PKLot, CNRPark+EXT, COWC, CVPark, UA-DETRAC, Smart Parking, KITTI, EuroCity, Park-UPB, UCCS, PUCPR+, GTI, P-ANDS, P-PArkID, VDIs, and MPII Parking. In dataset PKLot, 12,417 images were used from which 4800 where indoor images and 7617 images where outdoor images. In CNRPark + EXT dataset, 5000 images were indoor images, and 10,000 images were outdoor images. The number of research papers reviewed year-wise is shown in Figure 5.


**Figure 5.** Number of papers available year-wise.

Different types of techniques are used in parking detection system that include image-based parking detection, sensor-based parking detection, and others as shown in Figure 6a. In Figure 6b, using different datasets, parking system is categorized on the basis of accuracy, precision, and recall.




(**a**) (**b**)

**Figure 6.** (**a**) Parking detection technique types. (**b**) Metrics used.

The short description of metrics used in Figure 6b are listed below:

- Accuracy: Accuracy measures the overall correctness of the parking detection system's predictions. It quantifies the percentage of correct predictions out of all predictions made. A higher accuracy score indicates a more reliable system.

- Precision: Precision evaluates the system's ability to make correct positive predictions. It quantifies the percentage of true positive predictions out of all positive predictions made. A higher precision score suggests that the system minimizes false alarms, making it suitable for applications where false positives are costly.
- Recall: Recall, also known as sensitivity or true positive rate, assesses the system's ability to correctly identify all positive instances. It quantifies the percentage of true positive predictions out of all actual positive instances. A higher recall score is crucial when it is essential to minimize false negatives, ensuring that no parking spaces are overlooked.

In Figure 6b, each segment of the donut graph represents the count of research papers that predominantly focus on one of these three metrics. This categorization helps in understanding the emphasis of various studies within the field of smart city parking detection. By analyzing the distribution of papers across these metrics, we gain insights into the priorities and trends in the development of parking detection methods for smart cities.

## 5. Automatic Parking

In automated parking systems (APS), cars are stacked vertically to conserve space. It is feasible to transport cars from the entrance to their parking area without the driver being present thanks to the innovative designs of these systems. Along with the automatic parking system, these vertical parking structures are also known by other names:

- Automated parking facility (APF): The goal of an automated (car) parking system (APS) is to minimize the amount of space and volume required to park cars. In order to increase parking places while using the least amount of land possible, an APS offers parking for cars on many floors stacked vertically [66].
- Mechanical parking: Mechanical parking refers to a parking system that uses techniques like multi-story garages, automated parking systems, stack parking, etc., to reduce the overall amount of space needed to park the vehicles. These techniques are typically powered by hydraulic or electrical devices [67].
- Car parking system: A car parking system is a mechanical device that increases the number of parking spaces in a lot. Electric motors or hydraulic pumps are frequently used to power parking systems, which move cars into a storage position. In comparison to a conventional facility with the same capacity, automatic multi-story automated car park systems are less expensive per parking space, likely to require less building volume, and typically require less ground area [68].
- Robotic parking garage: PSs are helpful because they help preserve space, enabling more cars to fit in a compact place. This is particularly true for parking systems that run completely automatically and do not require personnel to park cars. Each vehicle can be parked nearer to the following one because no one will need to exit their vehicles [69]. This technology combines sensors, radars, and cameras to assume autonomous control of certain parking chores or the entire parking exercise, allowing drivers safely and securely store their vehicle without damaging it or other automobiles parked nearby [70].
- Shuttle parking system: Using self-driving shuttles and lifts, this type of parking system parks and retrieves vehicles. Using the pallet exchanger or conveyor belts on the shuttle, the car is then transferred from the shuttle to the parking space, and vice versa, before being parked or picked up at the agreed location [71]. The shuttles store vehicles on racks that are perpendicular to the fixed rails on both sides while moving horizontally along fixed tracks in a single direction. Construction of the structure uses either concrete or steel racking [72]. Typically serving bigger parking capacities, shuttle systems span from single level to multi-level. The parking system is only suitable for basement and outdoor parking. In this system, the car pulls up to the lift's ground floor entrance. The car is taken to the floor by the elevator [73]. In order to pick up the automobile from the lift and deliver it to the assigned parking places, there

is at least one shuttle on each floor. The representation of the shuttle parking system is shown in Figure 7.

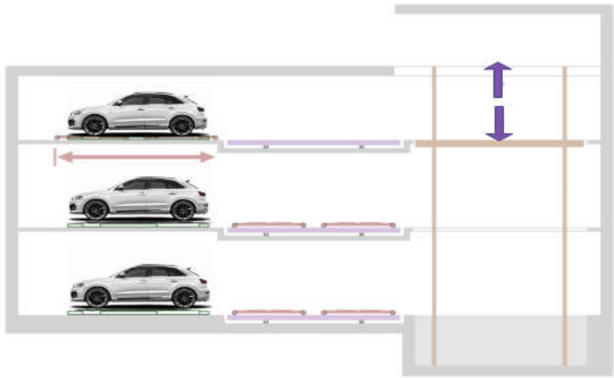


**Figure 7.** Shuttle parking system.

- Puzzle parking system: Jigsaw parking is a semi-automated method for parking and retrieving vehicles that uses combination pallets to move parking spaces both horizontally and vertically. It is a standalone parking system that can be easily customized to meet any property needs [74]. The number of parking places in a parking lot is increased by a mechanical part of the system. Electric motors or hydraulic pumps are frequently used in these parking systems to move vehicles into storage positions. This approach is suitable for parking outside. Matrix comparisons are used to separate these parking types. This is how the car pulls into the ground level parking slot. After that, the automobile is lowered into the lift using a car pickup pallet. The lift transports the car to various floors. To take the car from the lift and place it in the specified bays, there is at least one shuttle accessible on each floor. The entry and exit is from ground level. The representation of puzzle parking system is shown in Figure 8 [75].

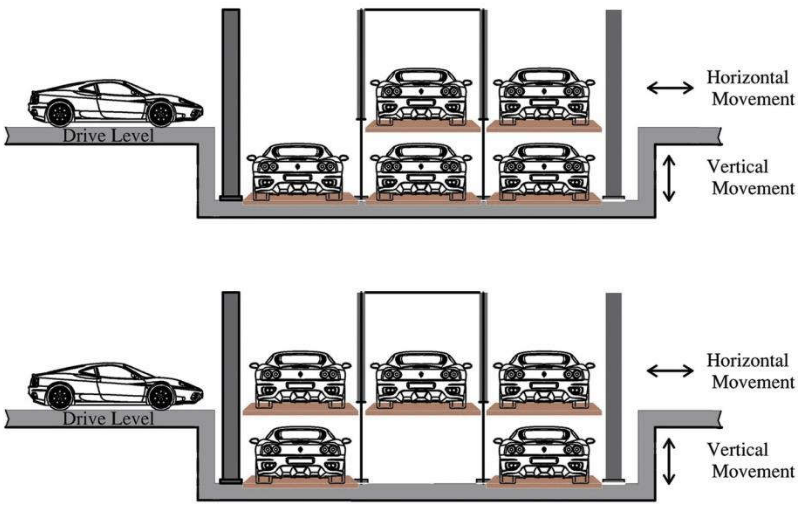



**Figure 8.** Puzzle parking system.

- Rotary parking system: Due to the circular parking structure, more than two cars can fit in the horizontal space. The building can house six automobiles in two spaces and, depending on the needs of the user, it can be modified to hold a greater number. For areas with little space, it is a practical solution. The automobile approaches the parking space on the ground floor in this configuration. Then, all the cars are turned in a clockwise direction until the first floor has an empty bay. Until the desired vehicle is at ground level, all the cars are turned clockwise to unload them. The driver now exits the system in order for the next car to be loaded or another car to be emptied [76]. Figure 9 shows the representation of rotary parking system [77].

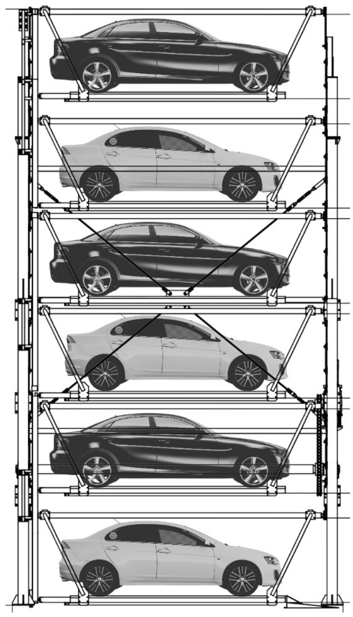


**Figure 9.** Rotary parking System [44].

- Stacker parking system: Instead of using a pallet, the stacker parking system uses a moving object called a "stacker" and offers short access and exit times for cars. The operation of this system is very similar to that of older ones, which is very convenient for the driver. Simultaneous vertical and horizontal movement can significantly shorten the time it takes to get in and out of the car. A robotic gadget moves the car to and from the lift/parking bay by pushing and pulling it [78].
- Automated guided vehicle (AGV) parking system: The AGV Parking System is meant to be put in the enclosed parking vault. This parking system can be constructed in a variety of conventional and unconventional configurations. It makes use of a number of levels above, on, and below slope to increase parking efficiency [79]. A mono-path system, which is limited to one lane of lateral movement along a steel rail, operates differently from this based system. AGV systems employ software technologies in order to move effortlessly over solid concrete slabs and around obstructions. This allows for quicker retrieval [80]. The technology will operate on solid polished concrete floors. It can move in both lengthwise and sideways directions along predetermined courses, as well as quickly rotate. AGVs drive beneath the vehicle platform in transfer cabins where vehicles are parked on platforms. They then elevate the platform, move it from the cabin into the system, and lower it. Warehouses that need automation are among its applications [81].
- Rail guided parking system: Vehicles are placed on pallets and positioned in parking modules. RGCs drive beneath the vehicle pallet, lift it, and then move the vehicle to move it from a parking module and into the system. The RGC may move side-to-side as well as forward and backward. RGC systems function effectively on firm concrete surfaces and can move longitudinally and laterally through tiny guide rails put on the floor [82–84].
- Crane parking system: Crane-parking systems in multi-level systems carry out the vertical journey with a distinct lift component. A single mechanism can move the vehicle that needs to be parked or retrieved both horizontally and vertically at the same time. The crane moves along tracks that stretch down the center aisle and are mounted to the floor and ceiling. The crane mechanism moves horizontally on rails that are typically situated on the floor and ceiling of the parking system [36]. Vehicles

that need to be parked and picked up are positioned on a newly constructed vertical lift platform. The system's main benefit for quickly arranging objects is the crane's ability to move in both the up–down and left–right directions at the same time.

- Silo parking system: The single, centrally positioned parking and retrieval mechanism is a feature of cylindrical silo systems. Parking lots for automobiles surround the center. One vehicle can only be manipulated at a time because the lifting/rotating mechanism that occupies the core and completes the positioning. Simultaneous axial and up/down placement is possible with silo mechanisms, which can move the vehicles swiftly [37]. Parking silos can also be erected above ground; however, they are best suited for locations with extremely poor soil conditions. While typically just one automobile can be parked or retrieved at a time, silo systems allow the use of one or more parking modules.

## 6. Comparative Study

In Table 1, a comparative study of image-based parking detection system is provided. It includes the details of the type of model used in the reference paper, year of reference paper, dataset used, number of images used in the model, accuracy, precision, and recall of the model, type of model used the paper, input size, and AUC of the model.

A thorough analysis of different parking management strategies is presented in this study, with a focus on how well suited they are to automation in smart cities. In Table 1, a comparison of parking detecting systems using images is presented. From the findings, it is observed that the deep learning model provides the highest precision of 99.77%. After this, DeepPS model provides a precision of 99.54% using 12,165 images dataset. On the basis of accuracy, it is observed that model SPFCN provides 98% accuracy using a dataset with 11665 images. The following are the important conclusions drawn from the analysis of various techniques that help to explain smart parking systems:

- Automation levels: Parking techniques have been divided into groups based on how automated they are, from low to high. High degrees of automation, such as those found in stacker parking and automated garages, have the ability to maximize space utilization but also come at a higher expense and with more complexity.
- Space efficient parking: The space efficiency of various parking techniques varies. In heavily crowded metropolitan locations, multi-level and AGV parking systems are desirable solutions since they are excellent space optimizers.
- Cost factors: The expenses involved in implementing each parking solution vary greatly. When compared to automated garages and AGV parking, rotary parking and silo parking are more reasonably priced.
- Installation difficulty: These approaches vary in terms of how difficult they are to deploy, with some, like puzzle parking, enabling simpler deployment. Advanced functionalities can be provided by higher complexity systems like rail guided and crane parking.
- Flexibility: We evaluated how well these techniques might be tailored to various parking conditions. Others, like puzzle parking, provide a more moderate level of versatility, while some, like multi-level parking, may have limited adaptability.

There are several possible routes for further research in this area:

- AI and IoT integration: To increase the effectiveness of smart parking systems, future research should examine how AI and the Internet of Things (IoT) may be combined. Real-time insights for improved parking management can be obtained using IoT-enabled sensors and AI-driven predictive analytics.
- Sustainability and green parking: Researching the environmental effects of various parking strategies and coming up with eco-friendly solutions has to be a top concern.
- User experience and accessibility: This involves creating intuitive mobile applications, direction systems, and accessible features for people with special needs.
- Security and privacy: Security and privacy issues are raised as a result of the collection and processing of data using smart parking systems. For smart parking solutions that

are to be widely used, it will be essential to look into reliable security measures and ensure data protection.

- Urban planning and policy: To create standards and laws that make it easier to integrate smart parking systems into municipal infrastructure, researchers should work with urban planners and lawmakers.

**Table 1.** Image-based parking detection system comparative study.

| Ref. No. | Year | Type of Model | Dataset | Number of Images | Accuracy | Precision | Recall | Model Type | Input Size | AUC |
|---|---|---|---|---|---|---|---|---|---|---|
| [1] | 2017 | CNN | Custome Dataset | 2702 | AlexNet 95% LeNet 93% | Not reported | Not reported | LeNet AlexNet | 1000 × 1000 pixels | Not reported |
| [2] | 2019 | Deep Learning | Custome Dataset | 5800 | 86.00% | 82.50% | 80.00% | 3D-CNN + LSTM | Not specified | Not reported |
| [3] | 2018 | CNN | Custome Dataset | 8336 | 90.00% | Not reported | Not reported | Sequential | 128 × 56 pixels | Not reported |
| [5] | 2021 | Graph Neural Network | PS2 | 12,165 | Not reported | 97.05% | 90.70% | - | 600 × 600 pixels | Not reported |
| [6] | 2021 | YOLOv3 | Custome Dataset | 4900 | 94.70% | 98.61% | 98.94% | Object detection model | - | Not reported |
| [10] | 2020 | Deep Learning | Custome Dataset | 22,817 | Not reported | 87.75% | 88.52% | MobileNetV2 YOLOv3 | 64 × 192 pixels 256 × 768 pixels | Not reported |
| [11] | 2016 | Deep Learning | CNRPark and PKLot | 12,000 | 98.10% | Not reported | Not reported | CNN (AlexNet variant) | 224 × 224 pixels | 98.90% |
| [12] | 2020 | DeepPS DMPRPS | PS2 + Synthetic images | 23,000 | Not reported | 95.25% 95.33% | 94.19% 97.39% | - | - | Not reported |
| [13] | 2018 | DeepPS | PS2 | 12,165 | Not reported | 99.54% | 98.89% | AlexNet YoloV2 | 416 × 416 pixels | 0.982 |
| [14] | 2020 | SPFCN | PS2 | 11,665 | 98.00% | 98.26% | 97.56% | SPFCN | 224 × 224 pixels | Not reported |
| [15] | 2019 | DMPR-PS | PS2 | 12,165 | Not reported | 99.42% | 99.37% | VGG-16 | 224 × 224 pixels | Not reported |
| [16] | 2019 | Deep Learning | Custome Dataset | 400 | Not reported | mAP = 60.2% | Not reported | Faster R-CNN | - | Not reported |
| [17] | 2020 | Deep Learning | Custome Dataset | 40,000 | Not reported | 98.72% | 99.14% | Yolov3 | 1280 × 720 pixels | Not reported |
| [18] | 2021 | Deep Learning | PS2 | 12,165 | Not reported | 99.77% | 99.77% | VGG-16 | 416 × 416 pixels | Not reported |
| [19] | 2018 | VH-HFCN | Custome Dataset | 4200 | Mean IoU 46.51% | Not reported | Not reported | MatConvNet | 640 × 480 pixels | Not reported |
| [21] | 2020 | CNN | Custome Dataset | Not reported | 97.80% | Not reported | Not reported | - | - | Not reported |
| [22] | 2021 | cGAN | HERV | 1240 | Not reported | 98.63% | 98.97% | cGAN and autoencoder | 360 × 240 900 × 350 pixels | Not reported |
| [24] | 2017 | PPHT | Custome Dataset | 3264 | Not reported | 98.80% | 91.70% | Progressive Probabilistic Hough Transform | 1600 × 1200 pixels | Not applicable |
| [25] | 2015 | - | Custome Dataset | Not reported | Not reported | Not reported | Not reported | Not reported | Not reported | Not applicable |
| [58] | 2020 | CNN | PKLot | Not reported | Not reported | Not reported | Not reported | Faster R-CNNYolo | - | Not reported |
| [60] | 2020 | CNN | COWC | 12,000 | 95% | Not reported | Not reported | Mask R-CNN | - | Not reported |

## 7. Conclusions

According to an analysis of various techniques, the majority of smart parking systems in smart cities rely on sensors like ultrasonic, AVM, proximity, and fish cameras, which drive up the cost of the system because these components are necessary for the system to function in each vehicle. In this paper, parking space locator algorithms and dashcam and fish-eye camera methodologies are reviewed. For the purpose of locating available parking spaces in dashcam films, neural network-based approaches have been developed in response to the proliferation of dashcams. Finally, integrating automation and smart technologies into parking management has huge potential for improving urban mobility and easing congestion. We can contribute to the creation of smart parking solutions that are more effective, sustainable, and user-friendly in the future's smart cities by tackling the specified study areas.

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