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Enhancing Urban Parking Management with SSD-Based Satellite Detection Systems

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Abstract **–** The rapid urbanization and exponential growth in vehicle numbers have significantly increased the demand for parking spaces in metropolitan areas, creating challenges for drivers and urban planners alike. Effective detection of available parking spaces is crucial, as it impacts traffic flow, environmental sustainability, public safety, and the efficient use of urban land. Studies show that a significant portion of urban traffic consists of vehicles searching for parking, leading to increased energy consumption, higher emissions, and more congestion. This paper explores the use of advanced parking detection systems, specifically leveraging satellite technology and single-stage object detection algorithm Single Shot Multibox Detector (SSD). By analyzing the performance of the SSD model in detecting empty parking spaces from satellite images, this study offers a comprehensive evaluation of its strengths and weaknesses in various scenarios. The findings contribute to the ongoing development of smart parking solutions, which are essential for reducing environmental impacts, enhancing safety, and improving the quality of life in urban environments. This study is among the first to assess the SSD model's effectiveness in this critical area of urban infrastructure.

Keywords – parking management, smart city, deep learning, object detection, SSD

I. Introduction

Modern urbanization has caused an exponential increase in the number of cars on the road. As a result, the demand for parking spaces in metropolitan areas has increased, posing a significant dilemma for both drivers and municipal planners. Detecting available parking spaces is more than just a convenience for drivers; it is an important part of urban infrastructure that affects traffic flow, environmental sustainability [1] and the overall quality of life in cities. One of the main reasons for detecting empty parking spaces is that it directly affects traffic congestion. According to studies, in many cities, 20 to 30% of urban traffic consists of vehicles searching for parking spaces [2]. This increases per capita energy consumption of residents in metropolitan areas [3], leading to higher carbon emissions [4] and gasoline consumption [5], as well as more air pollution [6] and traffic congestion on a regional scale. By accurately detecting available parking spots in cities, it can also significantly reduce the hours drivers spend looking for a place to park. This leads to better traffic, less pollution and less stress in city center traffic jams. Open parking spaces are also critically important for achieving better space utilization efficiency, and this has been a challenge in large cities for many years. Cities facing parking shortages need to make the best use of available land [7]. Parking lots and garages are often underused or unevenly used; some spaces are full, others are empty [8]. Real-time information on parking availability can be provided and better utilized through advanced parking detection systems [9].

Parking management is an important revenue stream for cities, and an inefficient matching system can easily mean that parking revenues are missed [10]. For example, urban areas where smart detector systems are available can make the most of parking spaces to ensure that the space is used and that revenues collected from customers are collected effectively [11]. This recognition can result in a potential increase in revenue that municipal governments can spend on other important urban infrastructure projects. Finally, it is not possible to ignore the safety component of detecting empty parking lots [12]. Finding an empty space in a large parking lot can sometimes lead to erratic driving behaviors, such as unexpected stops or lane changes, which increases the probability of traffic accidents [13]. These technologies reduce the probability of such incidents by directing cars directly to accessible spaces, which helps to create a safer parking environment. To summarize, the importance of detecting empty parking spaces goes far beyond practicality. It is an important part of contemporary urban infrastructure that affects public safety, economic efficiency, land use, environmental sustainability and traffic management [14]. As cities expand and the number of vehicles on the roads increases, finding effective and smart parking solutions will become increasingly important. By investing in advanced parking detection systems, cities can reduce their environmental impact, improve the quality of life of residents and create more sustainable, efficient and safe urban environments.

The detection of objects, structural analysis, and identification of existing parking areas using satellite systems [15] are crucial steps in urban planning and the development of smart cities. Satellite technology can greatly minimize the time vehicles spend searching for parking spaces, resulting in reduced traffic congestion and pollution. Drivers can be guided directly to available spaces by providing real-time data to navigation systems or mobile applications, thus optimizing routes and avoiding unnecessary journeys. Satellite-based parking detection systems also help with more effective urban planning and management. Urban planners can use the data obtained by these systems to study parking trends, identify high-demand locations, and make informed decisions about infrastructure development, such as building more parking spaces or implementing dynamic pricing models. This system can also be applied to driverless vehicles that rely on precise data for navigation and parking. As autonomous vehicles become increasingly common, the ability to autonomously detect and navigate to available parking spaces will be critical to their mainstream acceptance.

Single Shot Multibox Detector (SSD) [16] and You Only Look Once (YOLO) [17] are prominent single-stage object detection algorithms known for their efficiency and speed in real-time applications. Unlike two-stage detectors, which first generate region proposals and then classify them, single-stage detectors like SSD and YOLO directly predict bounding boxes and class probabilities in a single forward pass of the network. SSD excels in detecting objects at different scales by employing a series of convolutional filters, each responsible for detecting objects at varying sizes. YOLO, on the other hand, divides the image into a grid and predicts bounding boxes and class probabilities for each grid cell, enabling rapid and accurate object detection. Both models are widely used in applications that require real-time processing, such as autonomous driving, where quick identification of pedestrians, vehicles, and other road hazards is crucial, and in surveillance systems, where timely detection of objects can enhance security and monitoring effectiveness. Their ability to balance speed and accuracy makes them ideal for tasks where computational resources and time are limited, but reliable detection is essential.

In this study, a detailed analysis of the detection performance of the SSD model is performed for the detection of empty parking spaces from images of parking areas captured from satellite systems. The detection capabilities of the SSD model in various scenarios are evaluated comprehensively. In addition, the performance parameters of the algorithm in question are measured and the performance of the SSD model is analyzed quantitatively. As a result of the measurement, the strengths and weaknesses of the detection capability of the SSD model are evaluated comprehensively. In this context, the study is one of the first applications that evaluates the SSD model in the detection of empty parking spaces.

II. Materials and Method

A. SSD Network Structure

The SSD model can be examined in three main parts: the backbone network part, the original bounding box generation part, and the convolution estimation part. In applications, it can be seen that the backbone network part is divided into the basic network and the additional feature extraction layer. The first operation in the working principle of the algorithm is to feed the images to the deep neural networks in order to extract the features of the images. Then, default frames are designed by extracting feature maps at different scales. Then, the features in the frames are extracted to estimate what the object to be detected is and its location. Finally, Non-Maximum Suppression (NMS) is used to select the prediction that is most compatible with the real target frame. NMS is a technique widely used in object detection and computer vision applications. If there is more than one prediction box for a detected object, it eliminates the extra boxes and selects the box with the highest accuracy rate. This application of NMS prevents overlapping in predictions and multiple predictions for a single object.

The network architecture of the SSD model is shown in Fig. 1. The network architecture generally consists of a main network and additional layers. The main network of SSD is created using a pre-trained convolutional neural network that extracts features from images [18]. The most commonly used basic network is VGG-16. VGG-16 is a convolutional neural network with a weight layer and consists of several convolutional layers and max-pooling layers. Each of these layers has a specific filter and extracts feature maps from the input image. The last layers of VGG16 consist of fully connected layers, but in SSD, additional convolutional layers are added instead of these layers. Each of these layers added after the main network produces feature maps at different resolutions and thus plays a role in recognizing objects of different sizes. SSD adds prediction layers for each feature map. These layers determine the possible classification for each position and the prediction boxes corresponding to the classification.

B. Loss Function

The SSD loss function combines the classification and location loss to optimize both the classification accuracy and location accuracy of the object detection model. These two loss components constitute the total loss function. The classification loss estimates whether each default box belongs to any class. This loss is usually calculated as follows:

$$L_{cls}(x,c) = -\sum_{i\in Pos} x_{ij} \log(c_i) - \sum_{i\in Neg} \log(c_0) \quad (1)$$

Positive examples predict local object classes, while negative examples predict background classes.

Location loss estimates how much each default box overlaps with the real object box. This loss is usually calculated as L1 or L2 loss and is expressed as follows.

$$L_{loc}(x,l,g) = \sum_{i\in Pos} x_{ij}\, smooth_{L1}(l_i - g_i) \quad (2)$$

where, the term $smooth_{L1}(z)$ in (2) is defined as:

$$smoooth_{L1}(z) = \begin{cases} 0.5z^2, & \text{if } |z| < 1 \\ |z| - 0.5, & \text{otherwise} \end{cases} \quad (3)$$

The total loss is calculated as the sum of the classification and location loss and is as follows:

$$L(x,c,l,g) = \frac{1}{N}\left(L_{cls}(x,c) + \alpha L_{loc}(x,l,g)\right) \quad (4)$$

Here, N is the number of positive default boxes, and α is the weight coefficient used to determine the importance of location loss.

In SSD, the abundance of negative examples makes training inefficient. When faced with such a problem, the hard negative mining technique is used to solve the problem. This technique calculates a classification loss by selecting the subset of negative examples with high loss. Thanks to this technique, the network is trained with more efficient negative examples and its imbalance is reduced.

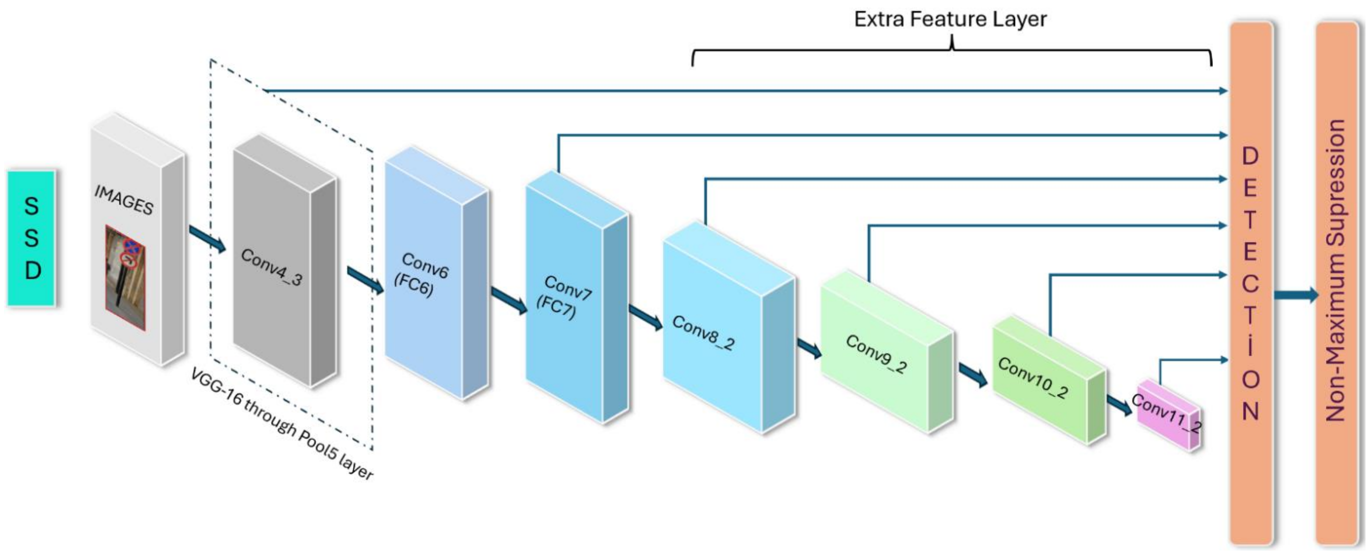

Fig. 1. Network architecture of the SSD model.

III. Results

A comprehensive dataset obtained from satellite images was created to evaluate the performance of the SSD model. The comprehensive creation of the dataset directly affects the performance of the model. The created dataset includes images from many challenging conditions. In order to investigate the effect of the shadow factor on the detection ability, images taken at different times of the day were added to the dataset. With the inclusion of images from different conditions, the dataset contains a total of 3750 images. The dataset was divided into three parts for the training, validation and testing stages of the model. In order to provide comprehensive training to the model, the majority of the dataset was used for training. Therefore, 2150:950:650 images were selected for the training, validation and testing dataset, respectively.

Fig. 2 presents various examples of the SSD model's detection of empty parking spaces across different scenarios, illustrating both its strengths and limitations. In example 1, an open parking lot with roughly half occupancy is shown. The parking spaces are demarcated by two parallel white lines, and the SSD model successfully detects the empty spaces when these lines are not obstructed by vehicles. However, in the lower-left section of the image, the model fails to detect an empty parking space due to the white lines being obscured by parked cars. This suggests that the visibility of parking lines is critical for accurate detection. Example 2 features an angled and somewhat distant view of the parking area, where the white parking lines are less distinct due to low image resolution. Unlike the previous case, the reduced visibility of the lines, rather than vehicle obstruction, affects the detection. Consequently, the model correctly identifies only the more clearly visible spaces.

Example 3 is similar to the first, with a top section of the parking area clearly visible, allowing the model to accurately detect the empty spaces. In other sections, irregularly parked vehicles obscure the parking lines, causing detection errors. This reinforces the importance of clear, visible lines for effective performance. In example 4, the model performs better overall, largely due to the image being taken from a lower altitude, resulting in sharper parking lines. Despite this, the SSD model still struggles to detect spaces between vehicles where the lines are less visible. Example 5 shows that while the model successfully detects most parking spaces, it occasionally draws bounding boxes smaller than the actual spaces, even including parts of a white vehicle in one of the parking spaces. This issue may arise because the vehicle's color closely matches the parking lines.

Example 6 involves a close-up view of the parking area with clearly visible lines. Similar to the previous example, the model mistakenly includes part of a white car in the bounding box and also detects an occupied space (with a black car) as empty. This error likely occurs because the parking lines on either side of the vehicle remain clearly visible, misleading the algorithm. Example 7 showcases an image captured from a low altitude with excellent resolution, allowing the SSD model to accurately detect most of the empty spaces. However, it again mistakenly includes part of a white car within a bounding box and identifies some areas incorrectly as parking spaces, possibly due to the similar color of the car and the parking lines. As expected, the model struggles in areas where vehicles obscure the parking lines. Finally, in example 8, the image is taken at a close angle, and the model successfully detects almost all the empty spaces. However, in some cases, it combines two adjacent empty spaces into one, likely due to the parking line between them being unclear.

The performance evaluation of the SSD algorithm for detecting empty parking spaces was carried out using four key performance metrics: precision, recall, mean Average Precision (mAP), and F1 score. In terms of precision, which measures the proportion of correctly predicted empty parking spaces out of all spaces identified by the model, the SSD algorithm demonstrated strong results with a precision score of 0.771. This indicates that approximately 77.1% of the detections made by the model were accurate and truly represented empty parking spaces, highlighting the model's reliability in minimizing false positives. The recall metric, which quantifies the proportion of actual empty parking spaces that were successfully detected by the algorithm, further supports the precision score. The SSD model achieved a recall value of 0.702, meaning it was able to correctly identify 70.2% of the true empty parking spaces present in the dataset. The close relationship between the precision and recall values indicates that the model is not only accurate but also effective at capturing a significant portion of the relevant empty parking spaces.

Fig. 2. Examples of vacant parking space detection using the SSD algorithm in various scenarios.

Another important metric, mAP, which is the average of precision values across all detection thresholds, was calculated as 0.744. This value represents the model's ability to maintain a high degree of accuracy over a range of detection scenarios, confirming that the SSD algorithm's detection capabilities are consistently strong across different levels of difficulty and various environmental conditions. Moreover, the F1 score, which is the harmonic mean of precision and recall, was measured at 0.735. The F1 score provides a balanced assessment of the model's performance by considering both the precision and recall values. This score highlights the overall effectiveness of the SSD model in maintaining a good balance between detecting as many empty parking spaces as possible while minimizing incorrect detections.

IV. CONCLUSION

In this study, the performance of the SSD algorithm was thoroughly evaluated for its ability to detect empty parking spaces in various scenarios using key performance metrics, including precision, recall, mean Average Precision (mAP), and F1 score. The results demonstrate that the SSD algorithm exhibits strong detection capabilities, with a precision score of 0.771, indicating a high accuracy rate in identifying true empty parking spaces. The recall score of 0.702 supports the algorithm's ability to capture a significant portion of actual empty spaces. The mAP value of 0.744 further emphasizes the model's consistent performance across diverse detection thresholds, while the F1 score of 0.735 reflects a balanced integration of precision and recall. These findings confirm the SSD model's suitability for automated parking space detection systems, where real-time identification of available spaces is crucial. The algorithm's robustness across varying environmental conditions and image qualities makes it an effective tool for parking management solutions. However, while the SSD algorithm shows considerable promise, there is still room for improvement, particularly in addressing the limitations related to occlusions and low visibility of parking lines, which may affect detection accuracy. Future work could focus on refining the model to enhance its performance under more challenging conditions, further solidifying its role in intelligent transportation systems and smart city applications.

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