Vision Transformers for Parking Space Detection

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Abstract

Parking space detection is a key component of intelligent transportation systems aimed at alleviating urban congestion and improving parking efficiency. This project investigates the application of Vision Transformers (ViTs) in comparison with traditional Convolutional Neural Networks (CNNs) for parking occupancy detection. Our goal was to develop a few-shot learning model capable of accurate segmentation using minimal labeled data, making it scalable to new parking environments without extensive annotation. We utilized the ACPDS (fully annotated) and PKLot (partially annotated) datasets and applied preprocessing to convert classification-style data into pixel-level segmentation maps. A pretrained DINOv2 ViT model was used as the feature extractor, followed by experimentation with both linear probing and a SegFormer-style decoder head for segmentation. The results show that the ViT-based architecture significantly outperforms CNN baselines, achieving high F1 scores even under challenging conditions such as occlusions, varying weather, and camera distortions. This work highlights the robustness, scalability, and practicality of Vision Transformers for real-world parking space detection systems. Source code: https://github.com/divyam-prajapati/Parking-Space-Detection.git

1. Introduction

Urban traffic congestion is a growing concern around the world, and a significant portion of this problem is due to inefficient parking systems. Studies estimate that more than 30% of city traffic is caused by drivers circling in search of available parking spaces. Traditional parking management systems, which often rely on sensors or manual surveillance, are costly, difficult to scale, and lack the flexibility needed for dynamic urban environments. Thus, there is a critical need for a more intelligent, scalable, and automated solution to accurately detect parking space occupancy.

1.1. Motivation

Computer Vision techniques, particularly Convolutional Neural Networks (CNNs), have been widely adopted for such detection tasks. However, CNNs typically rely on localized features and suffer performance degradation under real-world conditions such as occlusion, poor lighting, varied perspectives, and camera distortions. These limitations reduce their ability to generalize well across diverse environments without extensive data annotation and retraining.

Motivated by these shortcomings, our project explores the use of Vision Transformers (ViTs) — a class of models that use self-attention mechanisms to capture global image context — as a potential alternative. ViTs have demonstrated remarkable success in various vision tasks, particularly in scenarios requiring broader contextual understanding, and we hypothesize that these properties make them well-suited for robust parking space detection.

1.2. Overview of the System

Our approach begins by using DINOv2, a pre-trained Vision Transformer, as a frozen feature extractor. We first evaluate its performance using a simple linear classification head (linear probing). Building on this, we integrate a SegFormer-style lightweight decoder that includes convolutional layers, batch normalization, dropout, and nonlinear activations to enhance the spatial understanding of the model. This framework enables semantic segmentation of parking spaces into three classes: background, free, and occupied.

To evaluate generalizability and performance, we conducted experiments using two datasets: ACPDS (fully annotated, small-scale) and PKLot (larger, partially annotated). We converted the annotation formats to segmentation masks and standardized image dimensions. Our model is designed with few-shot learning principles in mind, aim-

ing to perform well with limited annotated data while generalizing to unseen parking scenarios. This makes it practical for real-world deployment, where data annotation is expensive and time-consuming.

Through this project, we demonstrate that Vision Transformers not only outperform traditional CNNs in accuracy but also offer superior adaptability and robustness under diverse real-world conditions, laying the foundation for more intelligent and scalable parking management systems.

2. Related Work

Several approaches have been proposed in recent years to tackle the problem of parking space occupancy detection using deep learning techniques.

De Almeida et al. introduced the PKLot dataset and applied classical CNNs like LeNet and AlexNet for binary classification of parking spots as occupied or vacant, marking one of the earliest large-scale visual benchmarks in this domain [2]. Martynova et al. conducted a thorough review and empirical evaluation of deep learning methods for parking detection, comparing CNNs, object detectors (e.g., Faster R-CNN, RetinaNet), and Vision Transformers (ViTs). They proposed a new EfficientNet-based architecture and highlighted the poor generalization of existing methods under varied visual conditions [1].

Sadek and Khalifa proposed a ViT-based parking detection system tailored for smart cities. Their system utilized attention-based encoding to achieve better results in scenarios with visual clutter and occlusion [4]. Nguyen and Sartipi developed a smart camera parking system using a ViT model combined with anchor-point detection. The model achieved high accuracy in both indoor and outdoor environments, showcasing the strength of transformers in spatial understanding [5]. Sharifai et al. proposed a hybrid Swin Transformer and DenseNet-121 architecture, demonstrating improved detection accuracy in occluded and low-light settings compared to CNN-only baselines [6].

Musabini et al. introduced a real-time multi-task cross-view transformer (MT F-CVT) that fuses fisheye images from multiple cameras to produce a semantic bird's-eye view of parking lots. Their model ran at 16 FPS and achieved high accuracy even on embedded systems [7]. Qiam et al. contributed a new dataset using both RGB and Near-Infrared (NIR) channels and demonstrated how using NIR enhances parking lot segmentation, especially in poor lighting conditions [8].

Cheng et al. proposed Mask2Former, a unified transformer-based architecture for semantic, instance, and panoptic segmentation [9]. The model introduces a masked attention mechanism that improves segmentation quality by focusing attention within predicted mask regions. Its modular design enables the reuse of a single framework across multiple segmentation tasks, making it suitable for semantic parking space analysis. Zhang et al. addressed the challenge of data scarcity in object detection with a knowledge reasoning-based few-shot approach [10]. Their framework incorporates semantic knowledge graphs to transfer object relationships, significantly improving detection accuracy in scenarios with limited annotated examples—directly relevant to real-world parking systems where exhaustive labeling is impractical.

tevanák et al. presented PKSpace, an open source pipeline for the detection of parking occupancy using low-cost visual sensors [11]. Their approach includes tools for annotation of parking spaces and image-based inference, demonstrating that even simple vision systems can be highly effective in structured parking environments. The FMPH Parking dataset, released by Matejov et al., provides annotated images of various parking scenarios captured under different weather and lighting conditions [12]. The dataset is especially valuable for evaluating parking occupancy algorithms in diverse real-world settings involving occlusion and visual noise. Ma et al. conducted an extensive review of parking space detection methods, categorizing them into sensor-based and vision-based approaches. The study highlights the advantages and limitations of various techniques, emphasizing the growing importance of vision-based methods due to their cost-effectiveness and scalability. The review also discusses the challenges in the field, such as varying lighting conditions, occlusions, and the need for real-time processing, providing a comprehensive overview that can guide future research and development in parking space detection systems [13].

These works collectively demonstrate the progression from simple CNN-based classifiers toward more complex and context-aware transformer architectures, motivating our exploration of Vision Transformers like DINOv2 with a SegFormer-style decoder for parking detection.

3. Dataset And Pre-processing

3.1. Dataset

In this study, we evaluate our parking space detection models using two distinct datasets: **PKLot** and **ACPDS**.

PKLot Dataset The PKLot dataset is a large-scale benchmark designed for parking space classification and detection tasks. It contains a total of 12,417 images captured from surveillance cameras at the Federal University of Paraná (UFPR) and the Pontifical Catholic University of Paraná (PUCPR) in Brazil. These images were recorded under various weather conditions, including 6,913 sunny, 4,162 overcast, and 1,342 rainy scenes. Although the data set offers significant environmental diversity and different camera perspectives, its annotations are *partially labeled*, providing only occupancy annotations at the box

level rather than dense segmentation masks. This makes it suitable for classification and detection tasks, but it requires additional pre-processing to be adapted for semantic segmentation models.

ACPDS Dataset The Annotated Car Parking Dataset (ACPDS) includes 293 images with full pixel-wise annotations, classifying each parking space as *free*, *occupied*, or *background*. This dataset introduces multiple environmental and visual challenges including 134 sunny, 132 overcast, 13 rainy, 34 foggy, 13 night scenes, and several occlusions (87 by vehicles and 35 by trees). Notably, all 293 images in ACPDS exhibit distortion due to fisheye lens usage, and each image is taken from a unique viewpoint. This makes ACPDS particularly suitable for generalization studies and few-shot learning scenarios where robustness to scene variation is critical.

Table 1. Image distribution across environmental conditions and occlusion types in the PKLot and ACPDS datasets.

Property / Dataset	PKLot	ACPDS
Sunny	6,913	134
Overcast	4,162	132
Rainy	1,342	13
Winter	0	0
Fog	0	34
Glare	0	1
Night	0	13
Infrared	0	0
Occlusion (car)	7	87
Occlusion (tree)	10	35
Distortion	0	293
Total images	12,417	293

3.2. Data Preprocessing

The pipeline begins with the acquisition of RGB parking lot images from either the PKLot or ACPDS datasets, as specified in the configuration parameters. Each image is resized to a fixed spatial resolution of 448×448 pixels to ensure consistency across the dataset. Images are normalized using standard mean and standard deviation values to optimize model performance. Corresponding segmentation masks are also resized to the same spatial dimensions and encoded as integer class labels, where each pixel is assigned to one of three categories: background, free parking space, or occupied parking space.

4. Method

The proposed framework for parking space segmentation leverages recent advances in vision transformers, specifically the DINOv2 and SegFormer architectures, to achieve robust and accurate pixel-wise classification of parking lot images. The overall methodology is illustrated in Figure 1, which provides a schematic overview of the system architecture and its key components.

4.1. Summary of the Architecture

The modular design of the framework, as visualized in Figure 1, allows for flexible experimentation with different segmentation heads while maintaining a consistent and efficient feature extraction pipeline. The use of a powerful transformer backbone, combined with either a lightweight linear classifier or a more expressive decoder, enables the system to achieve high accuracy in pixel-wise parking space detection.

4.2. Our Method

I) Feature Extraction with DINOv2 Backbone: As depicted in Figure 1, the normalized input image is first processed by a frozen DINOv2 backbone. DINOv2 is a self-supervised vision transformer model pre-trained on large-scale image datasets, and it serves as a powerful feature extractor in this framework. The backbone divides the input image into non-overlapping patches and projects each patch into a high-dimensional embedding space, resulting in a sequence of patch embeddings. For an input of size 448×448, the DINOv2 backbone produces 1025 patch embeddings, each of dimension 768.

The sequence of patch embeddings is then reshaped and permuted to reconstruct a lower-resolution spatial grid, typically of size 32×32×768. This step is crucial for restoring the spatial structure necessary for dense prediction tasks such as semantic segmentation. The reshaped tensor serves as the input to the segmentation head, which is responsible for mapping these features to class probabilities for each spatial location.

II) Segmentation Heads: The architecture supports two alternative segmentation heads, as shown in the upper and lower branches of Figure 1.

A) Linear Classifier Head: In the first approach, a simple linear classifier is employed, implemented as a 1×1 convolutional layer. This layer operates independently at each spatial location, projecting the 768-dimensional feature vector to the number of output classes (C). The result is a 32×32×C tensor, where each spatial location contains the class logits for the corresponding patch. This approach is

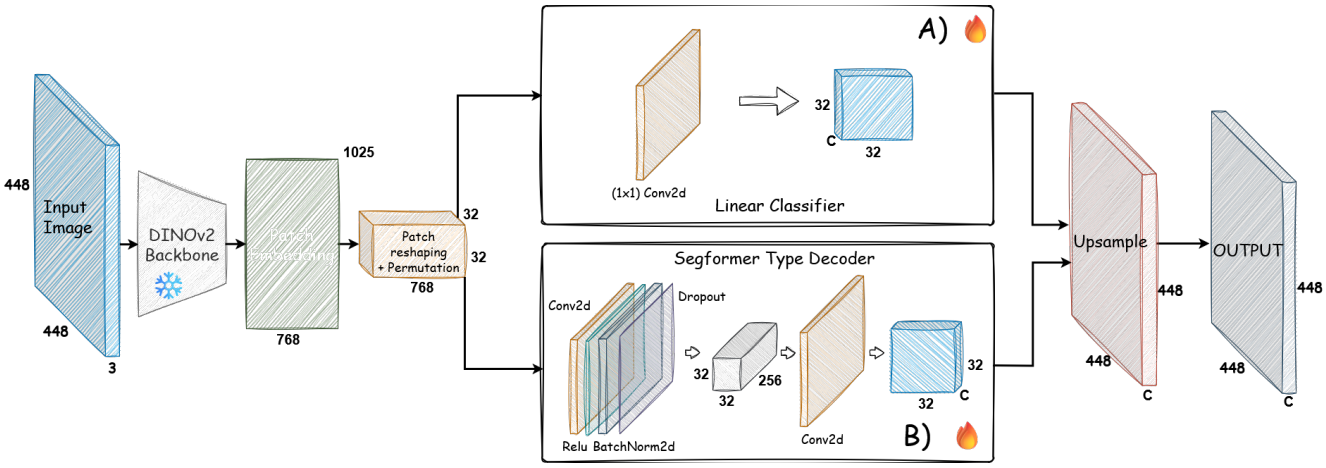

Figure 1. Overview of the proposed architecture. The input image is processed by a frozen DINOv2 backbone to extract patch embeddings, which are reshaped into a spatial grid. The features are then passed through either a linear classifier or a SegFormer-type decoder, followed by upsampling to produce the final segmentation mask.

computationally efficient and relies on the representational power of the DINOv2 backbone to provide discriminative features for direct classification.

B) SegFormer-Type Decoder Head: The second approach utilizes a more sophisticated SegFormer-style decoder. This decoder consists of a series of convolutional layers, batch normalization, ReLU activations, and dropout for regularization. The decoder first expands the feature dimension (e.g., to 256 channels), processes the features through non-linear transformations, and then projects them to the desired number of classes using another convolutional layer. This design allows for more complex feature aggregation and refinement, potentially capturing richer contextual information before the final classification.

III) Upsampling and Output Generation: Regardless of the segmentation head used, the resulting 32×32×C tensor is upsampled to the original image resolution (448×448×C) using bilinear interpolation. This step ensures that the output segmentation mask aligns spatially with the input image, enabling pixel-wise evaluation and visualization. The final output is a dense segmentation map, where each pixel is assigned a class label corresponding to background, free, or occupied parking space.

4.3. Training and Evaluation

I) Training: The model parameters of the segmentation head (and optionally the decoder) are optimized using the AdamW optimizer. The DINOv2 backbone remains frozen to preserve its pre-trained representations. The loss function employed is the cross-entropy loss, with the background class ignored to focus learning on the relevant parking space categories. The model is trained for a small number of epochs (typically 2–10 for demonstration), with evaluation metrics such as mean Intersection over Union (mIoU), mean accuracy, precision, and recall computed at regular intervals.

II) Evaluation Metrics: For comprehensive evaluation, we use the following metrics:

- **Mean Intersection over Union (mIoU)**: Measures the overlap between predicted and ground truth segmentation masks.
- **Precision**: Proportion of true positive predictions among all predicted positives.
- **Recall**: Proportion of true positive predictions among all actual positives.
- **F1 Score**: Harmonic mean of precision and recall, providing a balanced measure of accuracy that accounts for both false positives and false negatives.

These metrics offer a well-rounded perspective on both detection accuracy and segmentation quality across diverse conditions in both datasets.

5. Results and Analysis

We evaluated two model configurations for parking space detection:

- **Model A**: Utilized a simple linear probing head.
- **Model B**: Integrated a SegFormer decoder with a DINOv2 backbone.

Model B significantly outperformed Model A, achieving **F1 scores of 0.9246 on the ACPDS dataset** and **0.9749**

on the PKLot dataset when the background class was excluded. Including the background class slightly reduced the F1 scores, indicating that excluding the background during training helps the model better focus on detecting occupied and free parking spaces.

What makes these results particularly notable is that our model was trained on *partially annotated datasets*, while benchmark models in existing literature were trained on *manually extended and fully annotated datasets*, often over longer durations with hyperparameter tuning. Additionally, while these benchmark models generally perform classification over just **two classes (free and parked)**, our model was trained using **three classes: free, occupied, and background**, which introduces additional complexity but more accurately reflects real-world conditions.

Despite using less data and training for fewer epochs, our SegFormer + DINOv2 model achieved competitive performance with the benchmark models, demonstrating strong generalization across both datasets.

Table 2. F1 Scores Comparison Across Models on ACPDS and PKLot Datasets

Model	**ACPDS**	**PKLOT**
DeiT (pretrained)	0.8209	0.9928
PiT (pretrained)	0.7122	0.9818
ResNet50	0.8407	0.9926
MobileNet	**0.9343**	0.9991
AlexNet	0.8820	0.9990
VGG-16	0.8936	0.9985
EfficientNet-P	0.9125	**0.9995**
Ours (A) {exclude background}	0.5571	0.6044
Ours (B) {exclude background}	**0.9246**	**0.9749**
Ours (B) {with background}	0.7583	0.9258

As shown in Table 2, our SegFormer-based architecture (Model B) achieves F1 scores that are competitive with or exceed several well-known models including ResNet50, VGG-16, and EfficientNet-P. In particular, despite using datasets that were not fully annotated and requiring less training time, our model delivered results on par with MobileNet and EfficientNet-P, which are among the best-performing pre-trained models in the benchmarks. This highlights the robustness and effectiveness of the DINOv2 + SegFormer architecture in real-world parking space detection tasks.

6. Limitations & Challenges

Several practical challenges were encountered during the development and evaluation of this project. Variations in camera angle, caused by inconsistent or distorted perspectives from different placements, can significantly affect detection accuracy. Weather conditions such as sunlight, rain, snow, and fog often obscure the visibility of parking spaces. Visual obstructions from trees, poles, or vehicles can block parts of the image, making annotation and prediction more difficult. Furthermore, camera distortion, particularly from fisheye or wide-angle lenses, introduces spatial curvature that degrades spatial accuracy.

Other limitations include partial scene coverage due to restricted camera fields of view, and surface wear, such as faded or worn-out markings, which can confuse both models and annotators. Finally, regional differences in parking lot design and marking styles between countries introduce domain gaps that challenge the generalizability of models. Addressing these issues is essential for developing scalable real-world parking space detection systems.

7. Conclusion & Future Work

Conclusion

This work demonstrates the effectiveness of Vision Transformers, specifically DINOv2, for the task of detecting parking space occupancy. By combining a pretrained transformer backbone with a flexible decoder (either linear or SegFormer-style), our method achieves robust performance across challenging visual conditions. The SegFormer-based decoder, in particular, shows strong generalization and high segmentation accuracy on both the large PKLot dataset and the smaller, more focused ACPDS dataset. The experiments confirm that transformer-based segmentation architectures can outperform traditional CNN methods, particularly when dealing with variable lighting, occlusions, and weather conditions. Even with minimal fine-tuning, the frozen backbone paired with an appropriate decoder is capable of producing reliable segmentation maps suitable for real-world deployment.

Future Work

Future work could explore several avenues to further improve the robustness and scalability of parking space detection systems. One promising direction is the application of domain adaptation techniques to improve generalization in different parking environments, lighting conditions, and camera perspectives without requiring extensive retraining or annotation. Real-time deployment remains a challenge for transformer-based models because of their high computational demands. Techniques like pruning, quantization, and knowledge distillation could reduce latency for deployment on edge devices. In addition, incorporating auxiliary

data such as NIR, thermal, or LiDAR input may improve performance in low-light or occluded conditions by complementing RGB imagery with richer spatial and spectral information.

Another direction worth pursuing is the development of active learning or semi-supervised labeling frameworks, which can reduce annotation costs by selectively querying the most informative samples. Additionally, leveraging synthetic data generation and domain randomization may aid in creating robust models trained on simulated environments that transfer well to real-world settings.

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