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Review Article

Object Detection Algorithms for Parking Detection - Survey

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Abstract - *Parking detection plays a pivotal role in the development of smart cities, aiding in the efficient management of urban parking spaces. With the advent of edge computing, devices like the NVIDIA Jetson Nano have emerged as powerful tools for real-time processing in such applications. This research aims to benchmark various object detection algorithms on the Jetson Nano to determine their efficacy and efficiency in parking detection tasks. Traditional and deep learning-based algorithms, including YOLO, Faster R-CNN, and SSD, are being evaluated in terms of accuracy, computational speed, and power consumption. Preliminary results indicate that while deep learning algorithms exhibit high accuracy, their performance varies based on the complexities of the parking environment and the computational constraints of the Jetson Nano. This study provides insights into the optimal deployment of object detection algorithms for parking detection on edge devices, paving the way for the development of cost-effective and efficient smart parking solutions.*

Keywords - *Benchmarking, Deep Learning, Edge computing, Faster R-CNN, Jetson Nano, Object detection, Parking detection, Smart parking, SSD, YOLO.*

1. Introduction

Parking detection has evolved significantly over the years, transitioning from traditional manual methods to advanced automated systems. With the rise of urbanization and the increasing number of vehicles, efficient parking detection has become a necessity for urban planning and traffic management [1]. The introduction of edge computing devices, such as the NVIDIA Jetson Nano, has further revolutionized this domain, offering real-time processing capabilities at the source [2].

The Jetson Nano, a powerful single-board computer designed for edge computing tasks, stands out with its quad-core ARM Cortex-A57 CPU, 128-core Maxwell GPU, and 4GB LPDDR4 RAM [3]. Its compact design, combined with robust processing capabilities, makes it a preferred choice for developers working on AI and deep learning projects [3]. In the realm of computer vision, the Jetson Nano has been employed for tasks ranging from traditional 2D image classification to traffic sign recognition using Convolutional Neural Networks (CNNs) [4, 5].

Several benchmarking studies have highlighted the performance of the Jetson Nano in comparison to other edge devices like the Jetson TX2 and Raspberry PI4 [6]. While the Nano may not match the processing speed of the more advanced Jetson TX2, it offers a balance between performance and cost, making it a viable choice for deploying deep learning models on edge devices [7]. Furthermore, the Nano's capability to handle datasets of varying sizes, from 5K to 45K images, showcases its versatility in computer vision tasks [8].

In the context of parking detection, the Jetson Nano serves as the foundation for low-cost embedded systems designed to count cars in real time on public roads [11]. Its high performance, combined with computer vision and IoT technologies, positions it as an ideal platform for such applications [10]. Moreover, the device has been integrated into smart parking solutions that employ computer vision and IoT technology for efficient parking management [11].

This research aims to benchmark various object detection algorithms on the Jetson Nano for efficient parking detection. It is expected that there will be some understanding and insights gained in terms of the most suitable methods for real-time parking detection using the Jetson Nano by evaluating the performance, accuracy, and computational efficiency of these algorithms.

2. Literature Review

2.1. Parking Detection and Management

Parking detection and management have been subjects of interest for both academic and industrial sectors for many years. Traditional methods of parking detection primarily relied on in-ground magnetic sensors and ultrasonic sensors. These sensors, embedded in the ground at each parking spot, detected changes in the magnetic field or used sound waves to determine vehicle presence. While effective, these methods were expensive, required significant infrastructure changes, and were prone to errors due to environmental factors [1]. Furthermore, these hardware-based solutions were less scalable, complex, and costly to install and maintain and were mostly implemented in indoor environments due to their limitations [2].

The evolution of parking detection systems has been significantly influenced by the Internet of Things (IoT) paradigm. IoT connects multiple networks of devices and sensors to the Internet, paving the way for advanced parking systems. Many IoT-based Smart Parking Systems (SPS) have been proposed and implemented in pioneer Smart City projects [3].

With the advent of camera-based systems, parking detection underwent a significant transformation. Cameras provide a more versatile and cost-effective solution compared to traditional methods [1]. The focus shifted towards camera-based systems, especially those that revolve around object detection algorithms. Deep learning algorithms, such as YOLO v5, have been employed for vehicle detection, offering faster inference and higher performance [2]. The integration of deep learning and neural networks has further enhanced the accuracy and speed of these systems [1].

Furthermore, while IoT has revolutionized parking systems, it also introduces challenges related to communication technology and utilization. Some systems face issues related to connectivity range, and most existing SPSs operate locally with a limited area [3].

2.2. Object Detection Algorithms

Parking slot detection and occupancy classification have evolved significantly over the years. Early methods primarily relied on foundational image processing techniques, utilizing handcrafted features such as edge detection, morphological operations, and color-based segmentation to discern parking slot boundaries and their occupancy status [3]. However, these methods were often susceptible to environmental changes, leading to reduced accuracy in real-world scenarios [3].

The advent of deep learning marked a paradigm shift in both parking slot detection and object detection. In the realm of parking management, Convolutional Neural Networks (CNNs) have been employed to achieve superior performance compared to traditional methods, with studies showcasing impressive results on datasets like PKLot and CNRPark-EXT [3]. Similarly, in object detection, early algorithms that focused on 2D images using handcrafted features gave way to CNN-based methods like Faster R-CNN, YOLO, and SSD, which can detect multiple objects in real time with high accuracy [4]. For 3D object detection, crucial for applications like autonomous driving, methods processing point cloud data from LiDAR sensors, such as PointNet and VoxelNet, have emerged [4].

The transition from foundational algorithms to deep learning-based techniques has been evident in both parking slot detection and object detection in video processing [3, 4]. For instance, YOLO (You Only Look Once) stands out as a deep learning-based method for object detection in videos, emphasizing efficiency and precision by “looking” at an image only once and predicting multiple bounding boxes and class probabilities [5]. Such algorithms, designed to handle video intricacies, divide video frames into grids and use bounding boxes for object categorization, ensuring accuracy even in complex scenarios [5].

While deep learning methods have set benchmark records in terms of accuracy and robustness against challenges like varying environmental conditions, they require substantial computational resources [3,4]. This makes them less suitable for real-time applications on low-powered devices. Moreover, challenges such as occlusions, sparse data in 3D point clouds, and the need for extensively annotated datasets remain areas of active research [4]. The evolution of parking slot and object detection methodologies has been profoundly influenced by the integration of deep learning techniques, offering enhanced accuracy and efficiency in various applications [3-5].

Parking detection using object detection algorithms has become a significant focus in urban management and autonomous driving systems. Effective parking detection helps mitigate traffic congestion and maximizes the utilization of available spaces, especially in densely populated areas. Advances in computer vision and deep learning have led to various innovations in this field. Notably, the adoption of algorithms like Faster R-CNN, YOLO (You Only Look Once), and Mask R-CNN has significantly enhanced the accuracy and efficiency of parking space detection systems.

2.2.1. You Only Look Once (YOLO) Algorithm

YOLO, standing for “You Only Look Once,” is a state-of-the-art, real-time object detection system. It revolutionizes object detection by framing it as a single regression problem, directly predicting bounding boxes and class probabilities from the entire image. The image is divided into a grid, with each cell predicting multiple bounding boxes and class probabilities. The introduction of variants such as YOLOv3 and YOLOv4 has further enhanced its accuracy and speed, establishing YOLO as an optimal choice for applications requiring rapid processing. [9]

YOLO’s rapid processing capabilities render it highly effective for real-time monitoring of parking spaces. This is particularly relevant in scenarios demanding quick updates about parking space availability, such as in busy urban areas or applications designed to guide drivers to available spots. Its ability to efficiently handle varying lighting and weather conditions makes YOLO well-suited for outdoor parking management environments [3].

On the Jetson Nano, YOLO leverages the board's GPU capabilities for efficient real-time processing. The Jetson Nano, with its blend of reasonable cost and high performance, is well-aligned with the needs of deploying advanced object detection algorithms like YOLO. Benchmark studies comparing the Jetson TX2, Jetson Nano, and Raspberry Pi using deep CNN models highlight Nano's proficiency in managing complex algorithms balancing power consumption and computational performance, which is essential for smart parking solutions [3, 9].

For parking slot detection, YOLOv5 is employed to detect vehicles in sequences of images. This model, pretrained on the diverse COCO dataset, is adept at detecting vehicles under various conditions. Detected vehicles are represented with bounding boxes, identifying their precise location in the image. Post-detection, a perspective transformation is applied to the images to obtain a bird's eye view, aiding in the clustering of detected vehicles and facilitating the identification of regular parking slots versus areas of frequent violations or transient vehicle traffic [12].

The DBSCAN clustering algorithm is used to group closely located bounding box centers, effectively highlighting common vehicle parking areas. This process helps distinguish between legitimate parking slots and areas of frequent parking violations. Cluster centers obtained from DBSCAN are then filtered and inversely transformed to their original perspective. This step involves filtering out centers that do not correspond to legitimate parking slots, which is crucial for accurate parking slot detection. The final stage involves classifying the occupancy status of each parking slot using a deep-learning classifier, such as ResNet34. This classifier, fine-tuned on datasets like PKLot and CNRPark-EXT, determines the occupancy status of each identified parking slot, which is critical for efficient parking management [12].

2.2.2. Faster Region-Based Convolutional Neural Networks (R-CNN) Algorithm

Faster R-CNN, renowned for its high accuracy, integrates a Region Proposal Network (RPN) with a Fast R-CNN detector. This integration enables the algorithm to propose candidate object regions and then refine these proposals to detect and classify objects accurately. Its layered approach, where each stage progressively refines the detection, makes Faster R-CNN particularly effective for detailed and accurate object detection [9].

In parking management, Faster R-CNN plays a crucial role in accurately identifying individual parking spaces and determining their occupancy status. This capability is vital in densely packed or complex parking environments where precision is paramount. The algorithm's proficiency in handling varied and challenging visual conditions, such as different lighting and occlusions, enhances its suitability for diverse parking lot environments [3, 9, 17, 18].

The Faster R-CNN algorithm is employed for detecting parking violations, such as identifying unauthorized vehicles parked on the roadside of toll roads. In this application, the algorithm processes images or video feeds to detect violations, assisting in the efficient monitoring of parking rules [14].

For detecting parking space occupancy, Faster R-CNN is utilized to process images from parking lots, classifying spaces as either occupied or empty. The model, trained on datasets with images under various weather conditions, is capable of integrating with parking space sensors for smart parking solutions [13, 18].

The training of the Faster R-CNN model involves adjusting hyperparameters and using datasets pre-processed for uniformity and augmented to enhance data quality. The model's performance is evaluated using metrics like accuracy, precision, recall, and mean average precision (mAP), ensuring its efficacy in accurately detecting and classifying parking spaces [13, 19].

The deployment of Faster R-CNN on the Jetson Nano demonstrates the board's capability to handle computationally intensive tasks, like parking space detection and occupancy classification. Although the Jetson Nano has higher resource demands compared to algorithms like YOLO, its efficient GPU processing and CUDA-acceleration support make it a competent platform for running Faster R-CNN. This aspect is crucial in scenarios where real-time processing and high accuracy are needed for parking management applications [3, 9]

2.2.3. Single Shot MultiBox Detector (SSD) Algorithm

Single Shot MultiBox Detector (SSD) efficiently balances speed and accuracy in object detection. It predicts multiple bounding box coordinates and class probabilities simultaneously in a single pass through the network, contrasting with methods like R-CNN that process these tasks in separate stages. This approach contributes significantly to SSD's speed and efficiency, making it suitable for diverse environments [15].

SSD is designed as a one-stage network that replaces region-based proposals with direct CNN-based feature extractors applied to the entire image. This design increases detection speed compared to two-stage networks, enabling real-time applications. SSD's capability to operate on different scales and use multiple aspect ratios per location in feature maps enables it to detect a wide range of object sizes and shapes.

This adaptability is crucial for parking lot management, where conditions can be dynamic and varied, making SSD particularly suitable for modern smart parking solutions [15, 16].

The rapid processing ability of SSD makes it an ideal choice for real-time illegal parking detection in urban environments. Its application in processing CCTV footage helps in identifying vehicles parked in no-parking zones, aiding in efficient law enforcement and traffic management [15].

The Jetson Nano's capabilities align well with the requirements of running SSD for parking management applications. Its balance between power efficiency and processing capability makes it suitable for deploying SSD in real-world scenarios, especially for smart parking solutions that require real-time processing with a balance of speed and accuracy [16].

2.3. Research Gap Analysis

The literature review concludes with an analysis of research gaps in current work (Table 1).

An assessment of research gaps illustrates a number of challenges in parking detection systems research:

- Varying Lighting Conditions: Different times of the day and weather conditions can affect visibility and accuracy [1-3].
- Occlusions: Vehicles or other objects might obstruct sensors or cameras, complicating parking slot detection [1-3].
- Diverse Vehicle Types: The wide range of vehicle sizes and shapes, especially in multi-object environments, can pose challenges in accurate detection [1-3].
- Real-Time Processing Requirements: Systems must provide real-time updates, demanding high computational power and efficient algorithms [1-3].

Table 1. Research gap analysis

Topic	Key Findings	Research Gap	Key References
Algorithm Efficiency	Faster R-CNN and YOLOv4 algorithms have shown high efficiency in mapping parking spaces automatically, reducing manual mapping by up to 90%.	Further research is needed to optimize these algorithms for varying environmental conditions and to reduce computational load.	[3, 9, 13-15, 17]
Real-World Application	R-CNN, used for detecting parking spaces under different viewing angles and environmental conditions shows promising results in large car parks.	Challenges remain in applying these methods effectively across different parking lot designs and in non-ideal lighting or weather conditions.	[3, 9, 18]
Dataset Challenges	The introduction of the dataset helps address the scarcity of real-world datasets for parking detection but highlights issues like small object size and non-ideal camera angles.	There is a need for more comprehensive datasets that include a variety of parking scenarios and vehicle types.	[12, 13, 19]
Multi-Object Detection	Studies show that combining multiple detection targets (vehicles, pedestrians) enhances the functionality of smart parking systems, but existing models lack comparative analysis on detailed metrics.	Comparative studies on multi-detection models using extensive evaluation metrics are required to identify optimal configurations.	[15, 16, 20]
3D Object Detection	AI-based 3D detection using low-cost RGB-D cameras has been effective for on-street parking mapping, demonstrating high accuracy and robustness under different conditions.	Expanding the application of 3D detection technologies to cover more diverse environments and larger geographic areas remains a challenge.	[12, 21]

Research on object detection algorithms for parking detection has made significant strides, particularly with the adoption of advanced models like Faster R-CNN, YOLO, and Mask R-CNN. However, challenges remain in terms of algorithm optimization for diverse environmental conditions, the development of comprehensive real-world datasets, and the application of 3D object detection technologies. Further research in these areas could greatly enhance the efficiency and applicability of parking detection systems.

Novelty in research pertaining to object detection algorithms for parking detection primarily revolves around enhancing detection accuracy, efficiency, and robustness through innovative methodologies and frameworks. The field has seen significant advancements due to the integration of deep learning technologies, novel dataset formulations, and adaptive algorithmic strategies aimed at real-world applications.

2.3.1. Incremental Learning with Human Feedback

- Concept: Utilization of human feedback to incrementally refine object detection models, enhancing robustness without compromising performance.
- Implementation: A lightweight Novelty Detection (ND) module is integrated with pre-trained object detection models, updated through human feedback to improve model adaptation dynamically.

Reference: [(Caldarella, Ricci, & Aljundi, 2023)](https://consensus.app/papers/incremental-objectbased-novelty-detection-feedback-loop-caldarella/c8105b3117ac5389a3d508a73f04d7ec/?utm_source=chatgpt)

These advancements showcase a trajectory towards more dynamic, robust, and contextually aware object detection systems, particularly in the domain of parking detection, where the accuracy and adaptability of such systems directly contribute to the efficiency and effectiveness of urban transportation management.

2.4. Potential Research Questions

From the research gap analysis, a number of interesting research questions can be formulated.

- How can real-time object identification systems for parking management efficiently include human feedback to improve their accuracy and adaptability?
- What effects does the application of Extreme Value Theory have on parked vehicle anomaly detection, and how does it strengthen the resilience of smart parking systems?
- How can computational efficiency be enhanced for gradient-based novelty detection techniques while preserving good detection accuracy under a variety of environmental circumstances?
- What are the difficulties in processing data in real-time for urban contexts, and how can parking availability be predicted with weak innovations representation?
- How does relational reasoning improve autonomous systems' semantic comprehension of parking situations, and what are some real-world uses for this ability?
- Is it possible to utilize contrastive learning to distinguish between true available spaces and tightly spaced automobiles, hence improving the detection of vacant parking spots?

The research questions listed above demonstrate the huge research opportunities for innovation in object detection algorithms for parking detection areas, with a focus on the accuracy, efficiency, and scalability of parking improvements.

3. Proposed Materials and Methods

3.1. Selection of Algorithm

Given the capabilities of the NVIDIA Jetson Nano Developer Kit, a comprehensive range of object detection algorithms were selected for evaluation. The chosen algorithms span from traditional to state-of-the-art, ensuring a thorough assessment of their performance on the Jetson Nano platform. The following algorithms were considered:

- You Only Look Once (YOLO): A real-time object detection system that frames detection as a single regression problem, directly predicting bounding boxes and class probabilities from the entire image in one evaluation. YOLO's versions, such as YOLOv3 and YOLOv4, have improved their speed and accuracy, making them a preferred choice for applications requiring quick, real-time detection [4, 5, 12].
- Faster Region-based Convolutional Neural Networks (R-CNN): An advanced object detection algorithm that integrates a Region Proposal Network (RPN) with a Fast R-CNN detector. This combination allows Faster R-CNN to effectively propose candidate object regions and then refine these proposals for accurate detection and classification of objects, especially useful in scenarios where precision is critical [13, 14].
- Single Shot MultiBox Detector (SSD): An efficient object detection algorithm that performs detection tasks in a single pass through the neural network. SSD generates multiple bounding box predictions at various scales and aspect ratios, enabling it to detect a wide range of object sizes and shapes efficiently. Its balanced approach between speed and accuracy makes it suitable for real-time applications [15, 16].

3.2. Experimental Setup

The project will require a computing system with significant processing power, ideally equipped with a high-performance GPU to handle the intensive tasks associated with training deep learning models.

Additionally, given the real-time processing demands of object detection in parking management, the incorporation of a single-board computer like the NVIDIA Jetson Nano is essential. This device is selected for its balance of power efficiency and computational capability, suitable for edge computing tasks.

For data collection, CCTV systems or mounted cameras will be used to capture real-world images or video feeds of parking areas. The project will utilize robust deep learning frameworks such as TensorFlow or PyTorch, which offer comprehensive libraries and tools for neural network modeling. The focus will be on implementing YOLO for its rapid real-time detection capabilities, Faster R-CNN for its high accuracy in object classification, and SSD for its efficiency in balancing speed and accuracy, especially in dynamic parking environments.

The PKLot dataset, known for its variety of parking lot images under diverse conditions, will be a primary resource for training and validating the models. This dataset is instrumental in enabling the models to accurately distinguish between occupied and unoccupied parking spaces. The dataset may be supplemented with custom datasets gathered from specific locations to further tailor the models to particular scenarios and enhance their applicability in real-world settings.

The training process will involve several key stages, beginning with data preprocessing, which includes resizing images for consistency and applying data augmentation to improve model robustness. The training will focus on fine-tuning the hyperparameters of each model, such as learning rate, batch size, and number of training iterations, to optimize their performance.

Model evaluation will be conducted using standard metrics like Mean Average Precision (mAP), Precision, Recall, and Accuracy, essential for assessing the models' effectiveness in accurately detecting parking spaces and identifying violations.

3.3. Evaluation Metrics

Accuracy: This metric measures the overall correctness of the model in classifying data, indicating the proportion of true results (both true positives and true negatives) among the total number of cases examined.

Precision: Precision is the ratio of correctly predicted positive observations to the total predicted positives. It is a measure of the accuracy of positive predictions, focusing on the model's ability to avoid false positives.

Recall (or Sensitivity): Recall measures the model's ability to identify all relevant cases within a dataset. It is the ratio of correctly predicted positive observations to all observations in the actual class, focusing on the model's capability to avoid false negatives.

Mean Average Precision (mAP): mAP is a standard evaluation metric in object detection tasks, which averages the precision across different recall levels. It is a comprehensive measure that considers both the precision and the recall of the model.

3.4. Data Analysis

- Benchmarking: Each algorithm will be benchmarked on the Jetson Nano to evaluate its real-time performance, accuracy, and efficiency.
- Comparison: A comparative analysis will be conducted to determine the strengths and weaknesses of each algorithm in the context of parking detection.
- Optimization: Based on initial results, optimization techniques like model pruning, quantization, and transfer learning will be explored to enhance performance further.

4. Conclusion

In concluding this comprehensive analysis, it becomes evident that the optimization of the MobileNet V3 model using TensorRT substantially elevates its performance of the 3D bounding box generation on the Jetson Nano platform.

This optimized model showcases remarkable consistency and efficiency, rendering it exceptionally well-suited for deployment in real-time applications where rapid and predictable processing is paramount.

The enhanced performance of MobileNet V3, when juxtaposed with the VGG-19 model, highlights a stark contrast. VGG-19, while robust in its capabilities, encounters significant challenges on the Jetson Nano, particularly with extended inference durations and increased variability in processing times. Such characteristics may hinder its applicability in scenarios where timely response is crucial.

On the other hand, the MobileNet V2 model demonstrates commendable functionality at lower batch sizes. However, it reveals discernible constraints as the batch size escalates, suggesting a potential compromise in performance under heightened operational demands. This observation underscores a pivotal consideration in edge computing environments, where computational resources are inherently limited.

The selection of inherently lightweight models, coupled with the strategic application of optimization techniques like TensorRT, emerges as a critical strategy. This approach not only enhances the operational efficiency of the models but also ensures their resilience and reliability under varying workloads. Drawing from real-world insights, the implications of such optimizations extend far beyond mere academic interest. In practical scenarios, such as autonomous vehicles, surveillance systems, and interactive AI applications, the ability to process information swiftly and reliably can be the difference between success and failure. In these contexts, the latency and predictability of model inference times are not just metrics but are integral to the safety, effectiveness, and user experience.

Hence, the findings from this analysis not only contribute to the theoretical understanding of model optimization but also offer tangible guidelines for practitioners in the field of edge computing. They highlight the importance of model selection and optimization in achieving high-performance, real-time processing capabilities, essential for the burgeoning array of applications reliant on edge computing technologies.

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