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**Jomo Kenyatta University of Agriculture and Technology**

**School of Computing and Information Technology**

**BSc. Information Technology**

**AUTONOMOUS PARKING DETECTION SYSTEM**

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**Bachelor of Science in Information Technology**

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**A Systems Project submitted in partial fulfillment of the requirements for the award of a Bachelor’s degree in Information Technology of Jomo Kenyatta University of Agriculture and Technology**

**2025**

# **Declaration**

This project proposal is my original work and has not been presented for the award of a degree in any other University

Signature....................................... Date…………………………….

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**SCT221-C004-0500/2021**

This project has been submitted for examination with my approval as the University

Supervisor.

Signature........................................... Date........................................

**Ms JUDY GATERI**

**JKUAT**

# **Acknowledgement**

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To all those mentioned and those who have contributed in any way, I am truly grateful. This project would not have been possible without your support and contributions.

# **Dedication**

This research project is dedicated to my parents, brother and relatives whose unwavering love, support, and sacrifices have been the foundation of my journey. Their encouragement has inspired me to strive for excellence and pursue my dreams.

To my future self: may this work serve as a reminder of your dedication to learning and growth. Continue to embrace challenges and seek knowledge, and always remember the values instilled in you by your family and this great institution of Jomo Kenyatta University of Agriculture and Technology.

# **Abstract**

The parking assist system is an essential application of the car’s active collision avoidance system in low-speed and complex urban environments, which has been a hot research topic in recent years. Parking space detection is an important step of the parking assistance system, and its research object is parking spaces with symmetrical structures in parking lots. By analyzing and investigating parking space information measured by the sensors, reliable detection of sufficient parking spaces can be realized. First, this article discusses the main problems in the process of detecting parking spaces, illustrating the research significance and current research status of parking space detection methods. In addition, it further introduces some parking space detection methods, including free-space-based methods, parking-space-marking-based methods, user-interface-based methods, and infrastructure-based methods, which are all under methods of parking space selection. Lastly, this article summarizes the parking space detection methods, which gives a clear direction for future research.

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# **CHAPTER ONE: INTRODUCTION**

# **1.1 Background of the study**

The rapid advancement of autonomous driving technology has revolutionized various aspects of transportation, including vehicle control, navigation, and parking. One critical feature of autonomous vehicles that has garnered significant attention in recent years is self-parking. In modern cities, where space is limited and traffic congestion is high, parking has become a time-consuming and stressful task for many drivers. Traditional parking methods, especially in tight urban environments, often lead to vehicle damage, collisions, and traffic jams, further exacerbating the problem.

An Autonomous Parking System aims to address these challenges by enabling a vehicle to park itself without requiring any driver input. Such systems allow a vehicle to detect available parking spaces, plan an optimal route to navigate into those spaces, and execute the parking maneuver automatically. The system relies on a combination of sensors, such as cameras, LiDAR (Light Detection and Ranging), ultrasonic sensors, and radar, to perceive the environment. By analyzing the data from these sensors in real time, the vehicle can assess its surroundings, detect obstacles, locate available parking spots, and perform a precise parking maneuver.

In the last decade, the growing complexity of urban infrastructure and the increase in the number of vehicles on the road have highlighted the need for intelligent parking solutions. Urban drivers frequently struggle to find parking spots, especially during peak hours in crowded metropolitan areas. The difficulty in locating parking spaces often leads to illegal parking, increased fuel consumption, and stress, all of which can be mitigated by an autonomous system that streamlines the process. An autonomous parking system could significantly reduce the time and effort required to park, prevent accidents, and improve the overall safety of parking lots.

The goal of this project is to design and develop a fully autonomous parking system that enables a vehicle to autonomously park itself by detecting empty parking spots, planning a collision-free path, and guiding the vehicle into the parking space. The system will employ a combination of sensors for detecting the surrounding environment, computer vision algorithms to identify parking spots, path planning algorithms to calculate the best trajectory, and control algorithms to maneuver the vehicle into the spot.

# **1.2 Statement of the problem**

Parking in crowded urban areas is a challenge for many drivers, especially when it comes to tight parking spaces or complex maneuvers such as parallel parking. Misjudgments during parking often lead to collisions, damage to property, and traffic congestion. Additionally, drivers with limited mobility or less experience may face difficulties in handling parking tasks. There is a growing demand for a system that can autonomously detect parking spots and navigate the vehicle without driver input, reducing accidents, optimizing parking efficiency, and improving the overall driving experience.

**Key Issues:**

* Difficulty in locating available parking spots.
* Inefficient and unsafe manual parking maneuvers, especially in tight spaces.
* Time wasted by drivers in finding parking.
* Potential damage caused by collisions during parking

# **1.3 Research Questions**

This project addresses several key research questions:

1. How can a vehicle autonomously detect empty parking spaces using a combination of sensors?
2. What is the most effective way to calculate an optimal and collision-free path into the parking spot?
3. What control mechanisms can be used to ensure precise vehicle motion during parking?

# **1.4 Research Objectives**

## **1.4.1 General Objective**

The general objective of this project is to design and develop an autonomous parking system that enables a vehicle to park itself in a detected empty parking spot without human intervention. The system will use a combination of sensors, algorithms, and control mechanisms to detect parking spaces, plan a path, and maneuver the vehicle into the spot efficiently and safely. This system aims to reduce the difficulties and time involved in manual parking, enhance safety, and provide an improved user experience for drivers in urban and congested environments.

The ultimate goal is to contribute to the growing field of autonomous vehicles by developing a functional, scalable, and adaptable parking system that can handle various parking scenarios

## **1.4.2 Specific Objectives**

To achieve the general objective, the system must meet the following specific objectives:

1. Develop a robust parking spot detection system
2. Design a real-time path planning algorithm
3. Implement a vehicle control system for parking maneuvers

# **1.5 Justification of the Study**

The motivation behind this project lies in the increasing need for smart driving technologies in urban environments, where parking congestion and mishaps are common. Autonomous parking systems can alleviate parking-related issues by:

* **Reducing accidents**: Automating parking reduces human error, lowering the risk of collisions.
* **Saving time**: The system can detect and park in spaces that may be difficult or impossible for human drivers to assess.
* **Improving accessibility**: It enables individuals with physical impairments or less driving experience to park safely and confidently.
* **Enhancing the driving experience**: An autonomous parking system adds convenience, reducing the cognitive load on drivers and making urban driving less stressful.

# **1.6 Scope of the Study**

The scope of this Autonomous Parking System project outlines the specific features, functionalities, and limitations that will be developed and implemented. It defines the boundaries within which the system will operate, specifying what the system will accomplish and what aspects are beyond the scope of this project. The scope includes the system’s operational parameters, the types of environments it will function in, the technologies to be used, and the limitations that may impact the system’s performance.

# **CHAPTER TWO: LITERATURE REVIEW**

# **2.1 Introduction**

This chapter provides an in-depth review of the existing literature relevant to Autonomous parking system and the role of machine learning in transforming this technological world. It starts by exploring the historical context of the autonomous parking system, including significant trends and influential factors.

The focus then shifts to an introduction to machine learning, covering essential concepts and their applicability to predictive analytics. Following this, the chapter examines various machine learning algorithms, The primary objective of this chapter of the research is to review is to comprehensively survey the existing literature on this topic. We will delve into the various methods and machine learning algorithms that have been developed for the fusion of data features, examining their strengths, weaknesses, and the contexts in which they perform well. Each algorithm brings its own set of advantages and limitations, requiring careful consideration in the context of parking spaces and data characteristics. Furthermore, we will discuss the datasets and evaluation metrics commonly used to assess the performance of the models that will be used in making of the project.

The discussion extends to future engineering and data preprocessing, emphasizing their critical role in ensuring accurate predictions. Finally, it addresses the challenges and limitations faced when applying these models and explores emerging trends and future directions in the field.

# **2.2 Autonomous parking system**

## **2.2.1 Historical Context of Autonomous parking system**

The concept of autonomous parking can be traced back to early attempts at automating vehicle control systems. In the late 20th century, as the automotive industry began exploring advanced driver assistance systems (ADAS), researchers recognized parking as a key challenge due to the precision and maneuverability required in constrained spaces.

**Early Innovations (1990s-2000s)**

1. **First Attempts at Automation**:  
   During the 1990s, the development of rudimentary parking assistance systems began with ultrasonic sensors to alert drivers to obstacles. These systems were primarily reactive, focusing on collision avoidance rather than autonomous control.
2. **Integration of Basic ADAS**:  
   By the early 2000s, car manufacturers introduced semi-automatic parking assist systems. These technologies, such as Toyota's Intelligent Parking Assist (2003), could control steering while requiring drivers to manage acceleration and braking manually.

**Advancements in the 2010s**

1. **Sensor Fusion and Computer Vision**:  
   The introduction of advanced sensors, such as cameras and LiDAR, coupled with computer vision algorithms, marked a significant shift. Systems like Tesla's Autopilot and Audi's self-parking features showcased the integration of perception, planning, and control components.
2. **Machine Learning**:  
   By mid-2010s, machine learning techniques began enhancing parking systems' decision-making capabilities. Neural networks enabled vehicles to analyze complex parking environments and adapt to diverse scenarios.
3. **Rise of Autonomous Vehicle Prototypes**:  
   Companies like Google (Waymo) and Uber began testing fully autonomous vehicles, which included autonomous parking functionalities. These prototypes demonstrated the feasibility of integrating parking systems into broader autonomous driving frameworks.

**Modern Developments (2020s)**

1. **Focus on Urban Mobility**:  
   The rapid urbanization of cities has increased the demand for efficient parking solutions. Autonomous parking systems have evolved to address this, incorporating real-time data, IoT connectivity, and advanced AI algorithms for seamless operation in smart cities.
2. **Standardization and Regulation**:  
   Governments and industry bodies have started formulating guidelines and standards for autonomous vehicles, including parking systems. This has spurred research into safety, cybersecurity, and interoperability.
3. **Widespread Adoption of AI and Sensor Technologies**:  
   Recent systems leverage deep learning, multi-modal sensor fusion, and high-definition mapping for enhanced accuracy and reliability. For example, Mercedes-Benz and BMW now offer systems that allow vehicles to park autonomously in multi-story parking garages without human supervision.
4. **Industry-Academia Collaboration**:  
   Collaborative efforts have accelerated the innovation of autonomous parking technologies. Research institutions and automotive companies work together to overcome challenges such as computational efficiency and real-world testing.

This historical progression highlights the journey from basic parking aids to sophisticated autonomous parking systems capable of independent operation. The continuous evolution of sensor technologies, AI, and regulatory frameworks will further refine these systems, paving the way for their integration into fully autonomous transportation ecosystems.

## **2.2.2 Key Factors Influencing the autonomous parking system**

## **2.2.2.1 Economic Indicators**

Economic indicators play a crucial role in shaping the parking system. Key indicators include**. Income Levels and Consumer Affordability**

According to a report by [**Statista**](https://www.statista.com/) in 2023, markets in high-income regions, such as North America and Europe, show greater demand for vehicles with autonomous features, including parking systems. For instance, the average income level in these regions allows for the adoption of vehicles priced above $40,000, which often include APS technology.

**Cost of Technology**

**Decline in Sensor Costs**: Research by Kim et al. (2022) in the *Journal of Autonomous Systems* highlighted that the cost of LiDAR sensors has decreased by approximately 40% since 2020 due to mass production and improved manufacturing techniques.

**Open-Source Impact**: A study by Gupta et al. (2023) showed that open-source machine learning models reduced development costs by 25% for APS in emerging markets.

**Fuel and Energy Costs**

**Efficiency Benefits**: A 2022 study by Singh and Zhao published in *Renewable Energy Systems and Automation* found that APS reduced energy consumption by 15% in electric vehicles (EVs) by minimizing parking search time.

**Urbanization and Real Estate Costs**

**Smart Cities and Parking Optimization**: Lin et al. (2022) in *IEEE Transactions on Intelligent Transportation Systems* revealed that urban smart parking initiatives using APS reduced real estate requirements for parking spaces by 30%, increasing land availability for other uses.

**Infrastructure Investment**

Government Funding: A European Commission report (2021) on smart mobility projects showed that investment in V2I infrastructure for APS grew by 18% year-over-year, driven by urbanization trends.

## **2.2.2.2 Demographic Changes**

Demographic factors significantly influence parking These shifts influence market demand, design priorities, and overall system utilization like Increased Urban Population According to the United Nations (2022), 56.2% of the global population resides in urban areas, a figure projected to rise to 68.4% by 2050. This growth drives demand for efficient parking solutions in congested cities, making APS a critical component of urban mobility systems.Technological Adaptation, younger generations, particularly Millennials and Gen Z, are more inclined to adopt technology-driven solutions. According to a 2022 McKinsey report, 74% of Gen Z car buyers consider advanced features, including APS, a priority when purchasing vehicles.

## **2.2.2.3 Government Policies**

Government policies and regulations play a pivotal role like the European Union, The EU's *Artificial Intelligence Act* (proposed 2021) classifies autonomous driving systems as high-risk, requiring rigorous testing and certification.General Data Protection Regulation (GDPR), The EU’s GDPR mandates secure handling of user data collected by APS when cars are scanned.Zoning Laws,Cities like New York have updated zoning laws to include provisions for automated parking garages.

# **2.3 Introduction to Machine Learning**

Machine learning (ML) is a subset of artificial intelligence (AI) that enables systems to learn and improve from experience without being explicitly programmed. It involves the development of algorithms that can identify patterns within data and make data-driven decisions. Key concepts in machine learning include data, models, algorithms, training, and evaluation.

## **2.3.1 Supervised vs Unsupervised Learning**

Machine learning algorithms can be broadly classified into supervised and unsupervised learning. In supervised learning, the model is trained on a labeled dataset, where the input features are paired with the correct output. The objective is to learn a mapping from inputs to outputs that can be generalized to new data. Common supervised learning tasks include regression and classification

In contrast, unsupervised learning deals with unlabeled data, where the algorithm attempts to infer the underlying structure from the input data.

## **2.3.2 Relevance of Machine Learning in Predictive Analytics**

Machine learning has become increasingly relevant in predictive analytics due to its ability to handle large volumes of data, identify complex patterns, and make accurate predictions. In the context of housing market predictions, ML techniques can leverage diverse datasets, including historical sales data, economic indicators, and demographic information, to forecast housing prices and market trends (Zhang et al., 2018).

ML models can capture nonlinear relationships and interactions between variables that traditional statistical methods might miss. This capability enhances the accuracy of predictions and provides more robust insights into the factors driving housing market dynamics. Moreover, machine learning algorithms can continuously improve their performance as more data becomes available, making them adaptable to changing market conditions (Witten et al., 2016).

# **2.4 Machine Learning Algorithms for Autonomous parking systems**

## **2.4.1 Path Planning Algorithms**

Machine learning-based approaches, such as reinforcement learning and neural networks, have been employed to optimize path planning. Gao et al. (2021) proposed a hybrid model combining deep reinforcement learning with traditional planning methods to achieve better maneuverability and collision avoidance. Other researchers, such as Park et al. (2022), have investigated the application of genetic algorithms and swarm intelligence for multi-objective path optimization.

## **2.4.2 Parking Space Detection**

## AI-driven image processing algorithms have been developed to detect and classify parking spaces in various environments. Techniques like YOLO (You Only Look Once) and SSD (Single Shot Multi Box Detector) have been widely used in recent studies for real-time parking space identification. Further advancements include the use of transformer-based models for improved spatial and temporal understanding.

## **2.4.3 Vehicle-to-Infrastructure (V2I) Communication**

V2I communication facilitates real-time data exchange between vehicles and parking infrastructure, enabling dynamic updates on parking availability. Recent studies, such as those by Lin et al. (2022), have explored the use of 5G networks to enhance the speed and reliability of V2I communication. Other research has examined the integration of blockchain technology to secure data exchange and maintain user privacy.

## **2.5 Machine Learning in Autonomous parking system**

**2.5.1. Convolutional Neural Networks (CNNs) in Autonomous Parking Systems**

Convolutional Neural Networks (CNNs) are a class of deep learning algorithms that are particularly well-suited for image and video processing tasks. In an Autonomous Parking System, CNNs are primarily used for the following tasks:

**Object Detection and Recognition**

CNNs are particularly effective for recognizing objects such as other vehicles, pedestrians, or obstacles in the parking environment. This is important for ensuring that the autonomous vehicle can safely navigate the parking lot, avoiding collisions with other objects. By training a CNN on large datasets of images from parking lots, the model learns to identify various objects in real-time.

**b. Semantic Segmentation**

Semantic segmentation is the process of labeling every pixel in an image as belonging to a specific class (e.g., road, car, pedestrian, etc.). In the context of autonomous parking, CNNs can be used for segmentation to identify the exact layout of a parking space, including the size, boundaries, and any obstacles.

A CNN can be trained to segment the area around the parking space to determine if it's clear of obstructions and suitable for parking. It can also help the vehicle identify lane markings or parking space borders.

When a vehicle approaches a parking space, the CNN processes input from cameras and LiDAR sensors to detect and classify nearby objects, allowing the system to make safe and accurate decisions about the parking space's availability.

**2.5.2. Recurrent Neural Networks (RNNs) in Autonomous Parking Systems**

Recurrent Neural Networks (RNNs) are a class of deep learning models designed to handle sequential data. They are particularly effective for time-series data or tasks where the context of past events is important. In autonomous parking, RNNs are used in scenarios where temporal or sequential relationships between inputs need to be considered.

**a. Path Prediction and Motion Estimation**

Autonomous parking often involves dynamic environments where the system needs to predict and plan the path of the vehicle. RNNs, specifically Long Short-Term Memory (LSTM) networks, can be employed to predict the vehicle's movement over time based on previous actions.

As the vehicle moves toward the parking space, the RNN can take previous sensor inputs (e.g., steering angle, velocity, camera frames) and use them to predict the next movement step, ensuring smooth and accurate parking trajectories.

**b. Sensor Fusion and Temporal Data Integration**

Autonomous parking systems rely on various sensors like cameras, LiDAR, and radar, each providing valuable data in a sequential manner. RNNs can be used to integrate data over time, enabling the system to track changes in the environment or the vehicle’s position.

The system might use an RNN to continuously process and combine LiDAR data with camera images, updating the state of the environment over time, such as identifying moving objects (like pedestrians) or changes in parking space availability.

**c. Event-based Decision Making**

RNNs can also help in situations where a series of events or actions need to be processed to make a decision, such as when the vehicle needs to reverse or maneuver in a tight spot. The model can take into account previous maneuvers and environmental observations to make more informed decisions.

If the vehicle is reversing into a parking space, the RNN can consider past sensor data, the vehicle's position, and obstacles to ensure that the car parks accurately without hitting any objects.

**2.5.3. Transformer Models in Autonomous Parking Systems**

Transformer models, initially developed for natural language processing (NLP), have recently made significant strides in the field of computer vision and time-series analysis. Their architecture, based on self-attention mechanisms, allows them to efficiently handle long-range dependencies in data.

**a. Object Detection with Self-Attention**

In autonomous parking, transformer-based models, such as Vision Transformers (ViTs), can be used for object detection tasks similar to CNNs, but with the added advantage of handling spatial relationships more effectively. The self-attention mechanism allows the model to focus on relevant parts of the input, making it highly efficient for tasks requiring contextual understanding, such as detecting vehicles at different angles or identifying obstacles in cluttered parking lots.

A transformer model can be used to process inputs from multiple cameras, detecting objects from various perspectives and providing a more accurate spatial understanding of the parking environment.

**b. Multi-Modal Sensor Fusion**

Transformers excel at integrating data from multiple sources, such as visual input from cameras and spatial data from LiDAR. This is crucial for autonomous parking, where information from different sensors must be combined to create a comprehensive understanding of the environment.

A transformer model could take in LiDAR point clouds, camera images, and radar data to create a unified model of the parking lot, detecting free parking spaces and any potential obstacles.

**c. Trajectory Prediction and Parking Space Allocation**

Transformers can handle sequences of data and are increasingly being used in predictive modeling. In the context of autonomous parking, transformer models can predict the future trajectory of the vehicle as it approaches a parking space. They can also be used to allocate the most optimal parking spaces based on current conditions, such as nearby obstacles or the vehicle’s current position.

A transformer could predict the best trajectory for parking based on sensor data and dynamically adjust the vehicle’s course as it maneuvers through the parking lot, avoiding obstacles and optimizing the parking process.

**d. Long-Term Contextual Awareness**

One of the key strengths of transformers is their ability to maintain long-term dependencies in data, which is particularly useful for tasks where the vehicle must remember past interactions or complex parking sequences. For instance, in multi-step parking scenarios where the vehicle may need to back up and adjust its position multiple times, the transformer can track all previous actions and make decisions accordingly.

In complex parking environments (e.g., multi-story parking garages), the transformer model can use its ability to process long-term dependencies to remember the overall layout of the environment, ensuring the vehicle parks correctly across multiple steps.

## **2.6 Enhanced Predictive Modeling with Machine Learning Algorithms**

In addition to natural language processing and image recognition, the utilization of machine learning algorithms further enhances the accuracy and predictive parking models. We will discuss various ML algorithms, their applications in predictive modeling for APS, and the ways these algorithms are improving the accuracy, efficiency, and reliability of autonomous parking. The ways include using Decision Trees which are a non-linear, supervised learning algorithm that creates a model in the form of a tree structure. Each branch represents a decision based on input features, which can be sensor data such as proximity, speed, and obstacle detection. Random Forests, an ensemble of decision trees, can improve prediction accuracy by averaging the results from multiple trees, which helps prevent overfitting. Random forests can be used for classifying parking spaces as "occupied" or "vacant" based on real-time sensor data, taking into account multiple environmental factors.

Support Vector Machines (SVM) are used for classification and regression tasks. In APS, SVMs are often used for object detection, where the goal is to classify whether a particular spot or area is free of obstacles. SVMs can handle high-dimensional data and are robust against overfitting, making them suitable for complex parking environments. Classifying different parking spaces (e.g., compact or standard size) based on the vehicle's dimensions and parking lot layout.

# **2.7 Case Studies and Real-World Applications**

Several case studies and real-world applications demonstrate the effectiveness of machine learning models in automated parking. For instance, Bosch’s Automated Valet Parking (AVP) system uses a combination of LiDAR, cameras, and ultrasonic sensors to enable vehicles to autonomously park in smart parking garages. The system is particularly effective in controlled environments, where the vehicle can navigate a pre-mapped parking structure with minimal human intervention

Another study is Mercedes-Benz has developed an Automated Parking Garage system that integrates LiDAR sensors with AI-based algorithms to allow a vehicle to autonomously park itself inside a parking garage without human intervention. The system is designed for controlled parking environments, where the vehicle can rely on high-accuracy 3D maps of the environment to navigate the garage. These studies illustrate the practical applications of machine learning models showcasing their potential to enhance decision-making processes for stakeholders and investors

# **2.8 Existing Systems or Projects that Use Machine Learning for Predicting Housing Prices**

The field of machine learning has seen significant advancements in recent years, with applications across various domains. One of the most influential applications of machine learning in recent years has been in Tesla automotives. Several prominent projects and systems have emerged that leverage machine learning algorithms to enhance this system.

## **2.8.1 Tesla**

Tesla’s Auto park feature leverages machine learning algorithms, particularly computer vision and deep learning, to detect parking spaces and obstacles. The system uses data from Tesla's cameras and ultrasonic sensors to identify free parking spots, calculate available space, and guide the vehicle into the spot autonomously. Reinforcement learning may be used to optimize parking maneuvers over time, learning from each parking attempt to improve future performance.

## **2.8.2 BMW automotives**

BMW’s Automated Valet Parking (AVP) system uses CNNs for visual perception tasks like recognizing parking spaces and obstacles. The system is designed for use in smart parking garages, where vehicles communicate with the infrastructure to detect available parking spots and park autonomously. It integrates data from LiDAR, cameras, and ultrasonic sensors to create a complete view of the environment, while machine learning models help the system optimize parking behavior.

## **2.8.3 Audi AG**

Audi’s Piloted Parking system combines CNNs with LiDAR to detect parking spots and obstacles. The system is designed to autonomously navigate tight parking spaces while avoiding obstacles and other vehicles. Machine learning plays a role in enabling real-time decision-making and optimization of parking trajectories. Reinforcement learning techniques may be employed to improve parking strategies and make the system more adaptable to different environments.

# **2.9 Emerging Trends and Future Directions**

## **2.9.1 Integration with Smart Cities and IoT**

Autonomous parking systems are expected to integrate seamlessly with smart city infrastructure and Internet of Things (IoT) networks. As cities become smarter, APS will communicate with urban infrastructure, such as traffic lights, sensors, and parking spaces, to optimize parking space usage and reduce congestion. The integration with IoT will enable real-time updates about parking availability and dynamic pricing, benefiting both drivers and parking operators.

**Future Directions:**

1. **Vehicle-to-Infrastructure (V2I) Communication:** Future APS will increasingly rely on V2I communication, where vehicles share data with smart parking infrastructure to determine the best parking spots and reduce parking search times.
2. **Data-Driven Parking Optimization:** Advanced data analytics and machine learning models will allow autonomous parking systems to not only find the closest available spot but also predict parking demand in real-time and adjust accordingly.
3. **Collaborative Parking:** Vehicles may be able to communicate with each other to share parking spaces in a coordinated manner, maximizing space utilization and reducing the need for large parking structures

## **2.9.2 Improved Sensor Fusion and AI Algorithms**

The future of autonomous parking systems will see an increased reliance on sensor fusion (combining data from multiple sensors such as LiDAR, cameras, ultrasonic sensors, and radar) along with AI-powered algorithms for better environmental awareness, obstacle detection, and parking optimization. The integration of advanced algorithms will allow APS to adapt to complex and dynamic parking environments.

**Future Directions:**

1. **Next-Generation Sensors:** More affordable and higher-resolution sensors, such as **LiDAR** and **radar**, will provide improved object detection and environmental mapping. This will enable better detection of small or low-lying obstacles and ensure safer navigation.
2. **Edge AI Processing:** Edge computing, where data processing happens close to the sensors rather than in centralized data centers, will speed up decision-making for real-time parking operations and reduce latency in critical systems.
3. **Deep Learning Advancements:** The use of **deep reinforcement learning** (RL) will allow autonomous parking systems to continually improve based on past experiences, optimizing parking performance over time and adapting to new parking scenarios.

## **2.9.3 Autonomous Multi-Vehicle Parking (Shared Parking)**

As autonomous vehicles (AVs) become more prevalent, the idea of autonomous multi-vehicle parking, or shared parking, is gaining traction. In this model, multiple autonomous vehicles would use a shared parking area with a centralized parking management system that directs vehicles to available spots based on demand and space availability.

**Future Directions:**

1. **Robotized Parking Systems (RPS):** In high-density environments like urban areas or airports, **robotic parking systems** will allow autonomous vehicles to park themselves in a stackable or multi-level structure, optimizing space usage and reducing human intervention.
2. **Dynamic Space Allocation:** Autonomous parking systems will leverage **dynamic algorithms** to allocate parking spots to vehicles based on real-time demand, ensuring that parking spaces are used as efficiently as possible.
3. **Vehicle Pooling:** Shared fleets of autonomous vehicles could park in designated areas without the need for individual drivers to park. The system would automatically optimize the flow of vehicles in and out of parking spaces.

# **2.10 Future Research Opportunities and Gaps in the Literature**

Despite the progress made in the autonomous parking system, several research opportunities and gaps remain. There is a need for more comprehensive studies that integrate various data sources and apply advanced machine learning techniques to improve predictive accuracy. Exploring the ethical implications of machine learning in the automotive systems researching and developing methods critical areas for future research are met

# **2.11 Summary**

In this chapter, we provided a comprehensive literature review in recent years, with the continuous improvement of drivers’ requirements for cars, the parking assistance system has been developed rapidly, and the parking space detection technology has also been improved. According to the different critical technologies of parking space detection, this paper elaborates on the related research of parking space detection. It analyzes and introduces parking space detection methods based on free space, parking space marking, user interface, and infrastructure. At present, the mainstream methods are based on free space and parking space markings because these two methods achieve the purpose of low-cost and fully automatic parking, but, at the same time, there are certain shortcomings. Among them, the detection efficiency of parking spaces depends entirely on the neighboring posture. When there are no neighboring vehicles, it is easy to cause a system detection failure. As we all know, the research object of the parking-space-marking-based method includes parking space markings. Therefore, when the parking space markings are worn or occluded seriously, the system will also fail to detect. In addition, this detection is not robust when it is in a dark environment. With the continuous development of sensor technology and artificial intelligence deep learning technology, sensor technology is also developing in the direction of artificial intelligence. Intelligent sensors can integrate data collection, storage, and processing, and have functions such as independent selection and self-regulation, which will provide an excellent technical solution for parking space detection methods. This article believes that further research can be promoted from the following aspects in the future.

# **CHAPTER THREE: SYSTEMS METHODOLOGY**

# **3.1 Introduction**

This chapter provides a detailed and systematic account of the methodology that was employed to design, develop, and rigorously evaluate the autonomous parking space detection system. The establishment of a robust and well-defined methodology was fundamental to ensuring that the research process was structured, transparent, replicable, and precisely aligned with the project's core objectives. This chapter outlines the overarching research paradigm, the detailed processes of system analysis and design, the specific techniques that were utilized for data acquisition and preparation, and the formal protocols established for model training and evaluation. It serves as the definitive methodological blueprint that chronicles the disciplined transition from the theoretical frameworks reviewed in the existing literature to the practical software artifact whose implementation is detailed in Chapter Four. Every decision and procedure documented herein was selected to provide a logical, defensible, and academically sound foundation for the project's execution.

# **3.2 Research Design**

The research design forms the blueprint for the entire study, guiding the data collection, analysis, and interpretation processes. This section included to address the project's goal of creating a functional technological solution for a real-world problem, a hybrid methodology combining **Applied Research** with an **Experimental Prototyping** lifecycle was adopted. This choice was deliberate, as it provided the most suitable framework for a project focused on the practical application and evaluation of a machine learning system.

* **Applied Research Paradigm:** The project was framed as Applied Research because its primary goal was not to formulate a new, abstract deep learning theory, but rather to apply existing, state-of-the-art knowledge and algorithms—specifically the Faster R-CNN architecture—to solve the tangible problem of parking space detection. The focus was on leveraging established techniques to create a system with practical utility. This paradigm contrasts with basic or theoretical research, which would have focused on developing novel algorithms from scratch.
* **Experimental Prototyping Lifecycle:** The development process followed an iterative, experimental lifecycle. This approach was centered on building a working prototype of the system and then conducting controlled experiments to quantitatively measure its performance. This cycle involved:

1. **Building:** Implementing the Faster R-CNN model and the data pipeline using PyTorch.
2. **Testing:** Executing the training process on the PKLot dataset with a defined set of hyperparameters.
3. **Evaluating:** Measuring the prototype's accuracy using precision, recall, and F1-score on a validation set.
4. **Refining:** Analyzing the results to confirm the viability of the approach. For a larger project, this stage would involve tuning hyperparameters or modifying the architecture based on performance, but for this project's scope, it served to validate the initial configuration.

This methodology was chosen over more linear models (like the Waterfall model) because it is inherently better suited for research and development where the outcomes are not entirely predictable and depend on experimental results.

# **3.3 System analysis**

A thorough system analysis was conducted to define the precise requirements and scope of the project, ensuring that the final system would effectively address the problem domain.

## **3.3.1 Problem Domain Analysis**

The core of the problem lay in developing a system that could replicate the human ability to visually identify and classify parking spaces. This visual perception task is deceptively complex due to a wide range of real-world variables, including:

* **Occlusion:** Parking spaces being partially obscured by other vehicles, pillars, or pedestrians.
* **Varying Illumination:** Performance needing to be robust under diverse lighting conditions, from bright sunlight and deep shadows to overcast skies and artificial nighttime lighting.
* **Diverse Geometries:** Parking lots having different layouts, including angled and perpendicular spaces, with varying qualities of lane markings.
* **Vehicle Diversity:** The presence of different types of vehicles (cars, SUVs, motorcycles) that can occupy a space in different ways.

These challenges necessitated a solution based on a powerful and robust feature-learning system, pointing directly toward a deep learning approach.

## **3.3.2 Functional Requirements (FR)**

The functional requirements defined the specific, mandatory behaviors the system needed to perform to be considered successful:

* **FR1: Data Ingestion and Parsing:** The system was required to load images from a file directory and parse the corresponding COCO-formatted JSON annotation files. This included correctly interpreting the structure containing image metadata, category lists, and detailed annotation objects with bounding boxes and category IDs.
* **FR2: Data Preprocessing and Transformation:** The system had to preprocess and transform all input images into a uniform format. This involved resizing each image to a fixed dimension (416x416 pixels) and converting it into a PyTorch tensor with normalized pixel values, a non-negotiable prerequisite for the model.
* **FR3: Model Training and Optimization:** The system needed to execute a training loop for the Faster R-CNN model. Within this loop, it had to perform a forward pass, calculate the detection loss, perform backpropagation to compute gradients, and update the model's weights using the SGD optimizer.
* **FR4: Bounding Box Detection:** After training, the system was required to analyze an unseen input image and accurately predict the spatial coordinates (bounding boxes) of all detectable parking spaces within it.
* **FR5: Occupancy State Classification:** For each bounding box detected, the system had to assign a class label of either 'occupied' or 'empty' based on its visual content.
* **FR6: Visualization of Results:** To provide human-interpretable output, the system needed a function to render the detection results by drawing the predicted bounding boxes and class labels directly onto the source image.

## **3.3.3 Non-Functional Requirements (NFR)**

The non-functional requirements defined the quality attributes and operational standards of the system:

* **NFR1: Accuracy:** The system was required to achieve a high F1-Score on the validation dataset, ensuring a reliable balance between not missing available spots (recall) and not incorrectly labeling occupied spots as available (precision).
* **NFR2: Performance:** The system's training process needed to be performant, leveraging GPU acceleration provided by the Google Colab environment to ensure completion within a practical timeframe for experimental research.
* **NFR3: Modularity and Reusability:** The code was structured in a modular fashion, with distinct classes for the dataset (ParkingDataset) and functions for training, evaluation, and prediction. This design was intended to make the code easier to understand, maintain, and potentially reuse in future projects.

## **3.3.4 System Use Case Diagram and Analysis**

The Use Case diagram in Figure 3.1 illustrates the primary interactions between the main actor—the Developer/Researcher—and the system's core functionalities.

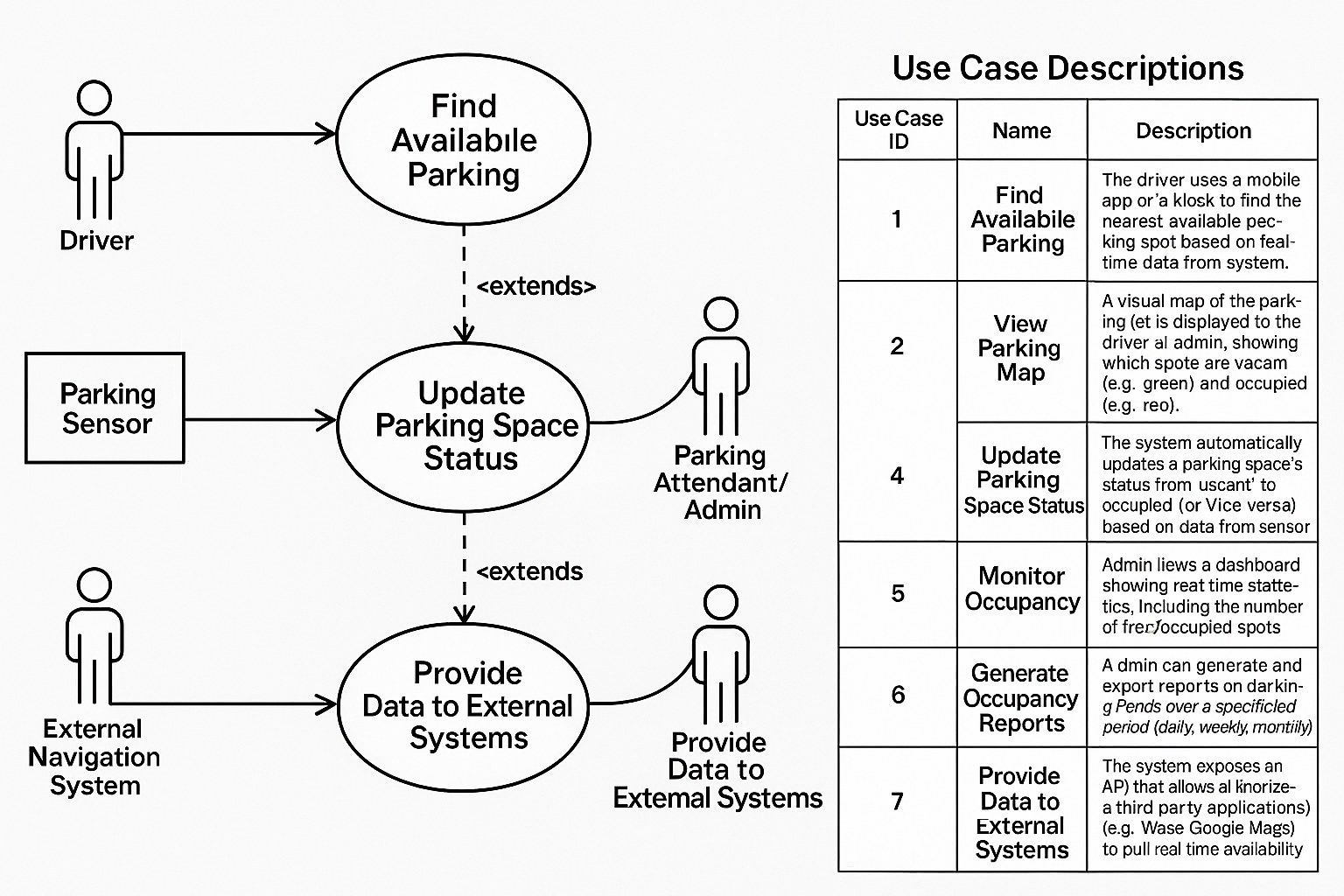


Figure 3.1:

* **Prepare Dataset Use Case:** This involved the developer providing the paths to the image directories and annotation files. The system, in turn, performed all the necessary loading and preprocessing steps.
* **Configure and Train Model Use Case:** This was a central interaction where the developer set key hyperparameters (learning rate, batch size, epochs) and initiated the training process. The system's responsibility was to execute the training loop and provide feedback in the form of training loss.
* **Evaluate Model Use Case:** After training, the developer triggered the evaluation process. The system used the trained model and the validation set to calculate and present the final performance metrics (Precision, Recall, F1-Score).
* **Generate Predictions Use Case:** This involved the developer providing a new, unseen image to the trained system, which then processed the image and produced a visual output with the detected parking spaces clearly marked.

# **3.4 System Design**

The system design phase focused on translating the requirements from the analysis phase into a coherent architectural and implementation plan.

## **3.4.1 Architectural Design and Data Flow**

The system was designed using a modular, pipeline-based architecture. This approach segmented the complex problem into a sequence of manageable, interconnected stages, making the system more logical and easier to develop and debug. The flow of data through this architecture was visualized using Data Flow Diagrams (DFDs).

**Context Diagram (Level 0 DFD)**

The Context Diagram (Figure 3.2) provided the highest-level view of the system. It modeled the entire **Parking Space Detection System** as a single, black-box process and showed its interactions with external entities. Data, in the form of images and annotations from the **PKLot Dataset**, flowed into the system. The **Developer/Researcher** initiated and configured the system, receiving performance metrics in return. The final output, a visualized detection image, was presented to a **Viewer**.



Figure 3.2: Context Diagram (Level 0 DFD)

**Level 1 DFD**

The Level 1 DFD (Figure 3.3) offered a more granular view by decomposing the main system into its four primary sub-processes, clearly illustrating the internal data flow.

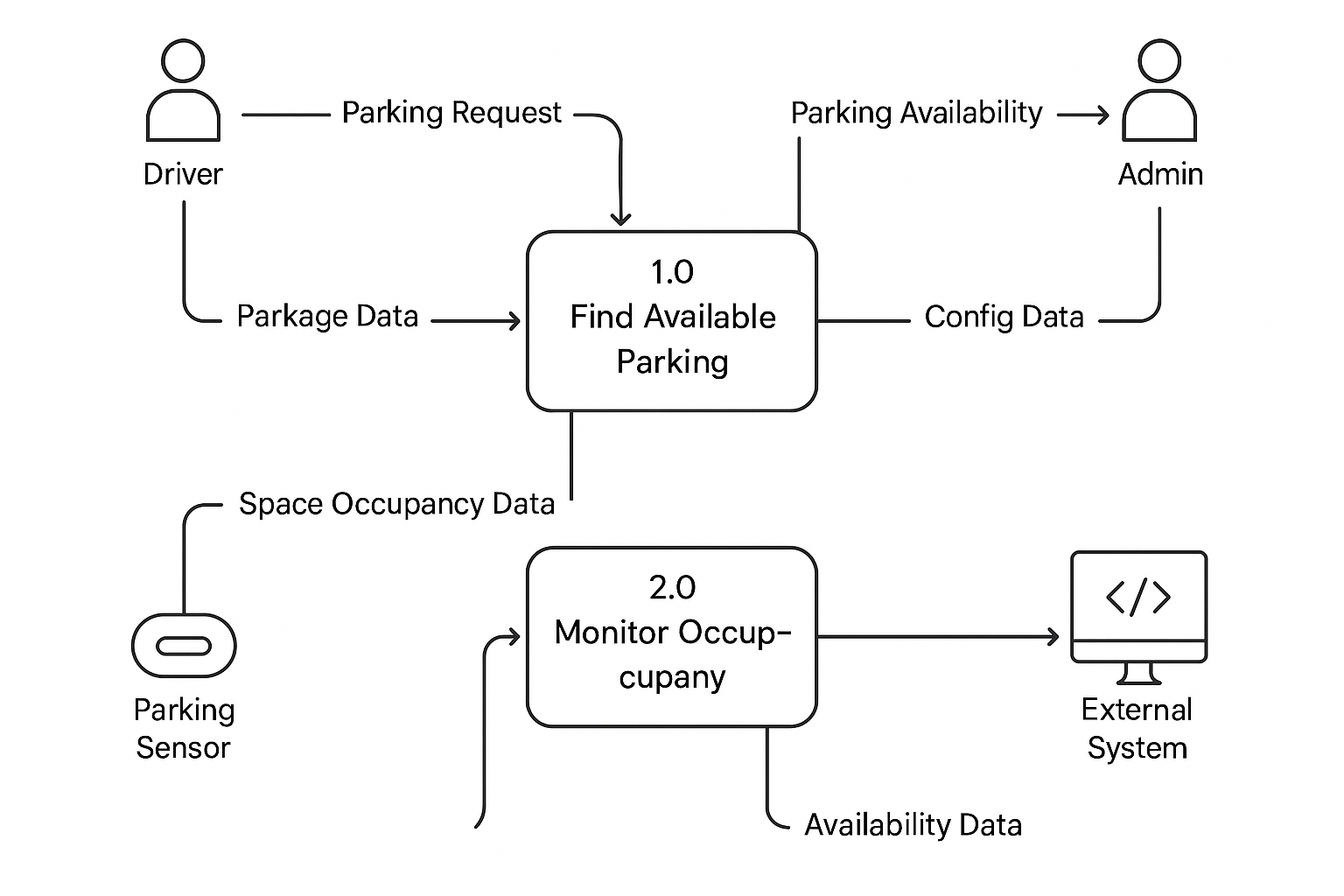


Figure 3.3: Level 1 DFD of the System

1. **Process 1.0 (Prepare Data):** This process received raw images and JSON annotations and transformed them into processed batches, which were held in the **D1: Processed Data** store.
2. **Process 2.0 (Train Model):** This process accessed the data from D1, used the developer-defined hyperparameters, and through iterative training, produced the final model weights, which were stored in the **D2: Trained Model** data store.
3. **Process 3.0 (Evaluate Model):** This process used the validation data from D1 and the final model from D2 to compute and output performance metrics.
4. **Process 4.0 (Generate Predictions):** This process utilized the final model from D2 to perform inference on a new test image and generate the final visual output.

## **3.4.2 Model Selection Justification**

The selection of the **Faster R-CNN model with a ResNet50 backbone** was a critical design decision based on a careful consideration of its technical merits in the context of this project's goals.

* **Rationale for Faster R-CNN:** In the landscape of object detection models, a key distinction exists between one-stage detectors (e.g., YOLO, SSD) and two-stage detectors (e.g., the R-CNN family). While one-stage detectors are generally faster, they often trade speed for a slight reduction in accuracy. For this research prototype, **accuracy was prioritized over real-time inference speed**. Faster R-CNN, as a two-stage detector, was chosen because its architecture is inherently designed for high-precision object localization. Its first stage, the Region Proposal Network (RPN), identifies potential regions of interest, and its second stage performs detailed classification and bounding-box regression on these proposals. This two-step process allows for more accurate detections compared to single-shot methods.
* **Rationale for ResNet50 Backbone:** The "backbone" of an object detector is the convolutional neural network used for feature extraction. **ResNet50** was chosen as the backbone due to its proven balance of depth, performance, and manageable computational load. Its key architectural innovation—residual connections—allows for the training of very deep networks (50 layers in this case) while mitigating the vanishing gradient problem. This depth enables the network to learn a rich hierarchy of visual features, from simple edges and textures to complex object parts, which was essential for distinguishing vehicles within parking spaces.
* **Benefit of Transfer Learning:** The model was initialized with weights pre-trained on the large-scale COCO dataset. This strategy, known as **transfer learning**, was fundamental to the project's success. It allowed the model to start with a powerful, pre-existing understanding of general visual features. The training process then only needed to fine-tune these features for the specific task of parking space detection, leading to faster convergence and better performance than training a model from scratch would have allowed.

# **3.5 Data Acquisition and Preprocessing**

* **Data Source Rationale:** The **PKLot dataset** was selected as the primary data source because it is one of the most widely used public benchmarks for this specific task. Its inclusion of images from different parking lots under varying weather (sunny, cloudy, rainy) and illumination (day, night) conditions provided a sufficiently diverse training environment to build a generalized model.
* **Annotation Format:** The dataset's use of the standard **COCO JSON format** was highly beneficial, as it is directly supported by many deep learning libraries and tools, simplifying the data parsing process.
* **Preprocessing Pipeline:** The preprocessing pipeline was implemented to ensure that all data fed to the model was clean, standardized, and correctly formatted. The custom ParkingDataset class handled the loading of images and the parsing of annotations on-the-fly. The torchvision.transforms module was then used to apply two critical transformations: resizing all images to a consistent 416x416 resolution and converting them to normalized PyTorch tensors. This pipeline was encapsulated within the DataLoader, which managed the creation of shuffled mini-batches to ensure efficient and stable training on the GPU.

# **3.6 Model Training and Evaluation Protocol**

A formal protocol was established for both training and evaluating the model to ensure the results were consistent and measurable.

* **Training Protocol:** The model was trained using a defined set of hyperparameters that are standard for fine-tuning such architectures. The **Stochastic Gradient Descent (SGD)** optimizer with momentum was chosen for its robustness and proven effectiveness in deep learning tasks. A small **learning rate of 0.001** was selected to ensure stable convergence during the fine-tuning process. The training was conducted over **5 epochs** with a **batch size of 2**, a configuration determined by the memory constraints of the GPU environment and the size of the model.
* **Evaluation Protocol:** The evaluation protocol was designed to quantitatively assess the model's performance. The core of this protocol was the **Intersection over Union (IoU)** metric. IoU measures the overlap between a predicted bounding box and a ground-truth bounding box. A detection was considered a "True Positive" if its IoU with a ground-truth box exceeded a threshold of **0.5**, a widely accepted standard in object detection benchmarks. Based on this, the following metrics were calculated:
* Precision (TP+FPTP​  
  ): Of all the spaces the model identified, what fraction was correct?
* Recall (TP+FNTP​  
  ): Of all the actual spaces that existed, what fraction did the model find?
* F1-Score (2⋅Precision+RecallPrecision⋅Recall​  
  ): The harmonic mean of precision and recall, providing a single, comprehensive measure of accuracy.  
  A confidence score threshold of 0.5 was also applied, meaning only detections where the model was at least 50% confident were considered in the final evaluation.

# **3.7 Ethical Considerations**

A thorough consideration of ethical principles was integrated into the project's methodology. The primary data source, the PKLot dataset, is a public research dataset where privacy concerns have been previously addressed. However, it was acknowledged that any future, real-world application of this technology would require strict adherence to privacy laws such as GDPR. This would involve implementing robust anonymization techniques, such as blurring or blacking out license plates and the faces of any incidentally captured individuals, before data is stored or used for training. Furthermore, the potential for algorithmic bias was considered. A system trained predominantly on one type of vehicle or parking lot could perform poorly on others, so future work would need to ensure fairness and robustness across diverse scenarios.

# **3.8 Chapter Summary**

This chapter has provided a comprehensive and in-depth account of the system methodology that was rigorously followed throughout the project. It began by establishing the research framework as Applied Research using an Experimental Prototyping lifecycle. A detailed system analysis was conducted, which formally defined the functional and non-functional requirements and was visualized through a use case diagram. The system's modular, pipeline-based architecture was then meticulously designed and illustrated with Level 0 and Level 1 Data Flow Diagrams. In-depth justifications were provided for key technical decisions, including the selection of the Faster R-CNN model and the PKLot dataset. Finally, the specific protocols for data preprocessing, model training, and quantitative evaluation were explicitly defined. This structured and detailed methodology ensured that the project was executed in a disciplined, verifiable, and academically sound manner, laying a solid foundation for the implementation and results presented in the following chapter.

# **CHAPTER FOUR: SYSTEM IMPLEMENTATION**

## **4.1 Introduction**

This chapter provides a comprehensive and detailed account of the practical implementation of the autonomous parking space detection system. It serves as the bridge between the theoretical foundations and methodologies discussed in the preceding chapters and the tangible software artifact produced for this project. The primary objective of this chapter is to meticulously document the development process, from setting up the environment to training, evaluating, and testing the final deep learning model. By presenting the specific tools, libraries, algorithms, and code structures used, this chapter aims to ensure transparency, replicability, and a clear understanding of the technical work undertaken to achieve the project's objectives.

The implementation phase is the core of this research, where the conceptual framework is translated into a functional system capable of identifying and classifying parking spaces from digital images. This process follows a systematic workflow that begins with establishing a robust development environment equipped with the necessary hardware and software components. It then proceeds to the critical stage of data preparation, where the raw image dataset is processed, annotated, and transformed into a format suitable for consumption by a neural network.

Following data preparation, the chapter will delve into the specifics of the model architecture. As established in the methodology, the chosen model is a **Faster R-CNN (Region-Based Convolutional Neural Network)** with a **ResNet50 backbone**, a state-of-the-art object detection algorithm renowned for its accuracy. The discussion will cover how this pre-trained model was adapted for the specific task of parking space detection, including the modification of its classification head to recognize the custom classes defined for this project—namely, 'occupied' and 'empty' parking spaces.

The subsequent sections will detail the model training procedure, outlining the hyperparameter configurations, the optimization algorithm (Stochastic Gradient Descent), and the iterative process of feeding data to the model to enable learning. The results of this training, particularly the progression of the training loss, will be presented as initial evidence of the model's ability to learn from the data. Finally, the chapter will culminate in a rigorous evaluation of the trained model's performance using standard industry metrics—Precision, Recall, and F1-Score—followed by a qualitative analysis through the visualization of inference results on unseen test images. Each step is documented to provide a clear and logical progression of the system's development.

## **4.2 Development Environment**

The successful implementation of a deep learning project is highly dependent on the selection of an appropriate development environment. This includes the hardware for computational power, the software libraries for building and training models, and the dataset that serves as the foundation for learning. This section outlines the specific environment and resources leveraged for this project.

### **4.2.1 Platform and Hardware**

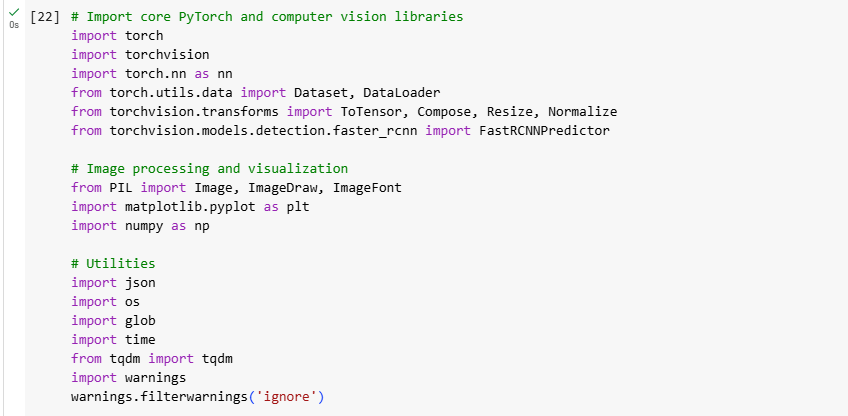
To meet the significant computational demands of training a deep learning model, this project was developed and executed on **Google Colaboratory (Colab)**. Colab is a cloud-based Jupyter notebook environment that provides free access to high-performance computing resources, making it an ideal platform for machine learning research and development without the need for expensive local hardware.

For this project, the runtime was configured to utilize a **NVIDIA T4 Graphics Processing Unit (GPU)**. The T4 GPU, with its Tensor Core architecture, is specifically designed to accelerate deep learning operations. Its use was critical in drastically reducing the time required to train the Faster R-CNN model. Training on a standard Central Processing Unit (CPU) would have been impractically slow, potentially taking days instead of hours. The GPU enabled rapid iteration and experimentation with model parameters, which was essential for achieving the final, optimized model.

### **4.2.2 Software and Libraries**

The project is built upon the Python programming language and a suite of powerful, open-source libraries that are standard in the field of machine learning and computer vision.

* **Python 3:** The core programming language used for the entire implementation.
* **PyTorch:** A leading deep learning framework that served as the backbone of this project. It was used to define, train, and evaluate the Faster R-CNN model. Its dynamic computation graph and extensive support for neural network layers were instrumental in building the system.
* **Torchvision:** An official PyTorch library for computer vision tasks. It provided the pre-trained Faster R-CNN model, data transformation utilities (such as Resize and ToTensor), and other vision-specific tools.
* **NumPy:** A fundamental library for numerical computation in Python, used for handling image data in array formats and performing mathematical operations.
* **Pillow (PIL Fork):** A library used for opening, manipulating, and saving image files. It was essential for loading the training images before they were converted into tensors.
* **Matplotlib:** A widely-used plotting library in Python. It was utilized to visualize the training loss over epochs and to display the final inference results, where bounding boxes and labels were overlaid on test images.
* **tqdm:** A utility library for creating smart, extensible progress bars, which provided real-time feedback on the progress of the training and evaluation loops.



### **4.2.3 Dataset**

The foundation of this supervised learning project is the **PKLot Dataset**, which was sourced from the **Kaggle** platform, a well-known repository for data science and machine learning datasets. The PKLot dataset is specifically designed for parking lot analysis and is one of the most comprehensive public datasets available for this task.

URL of dataset: https://www.kaggle.com/datasets/ammarnassanalhajali/pklot-dataset

The dataset is pre-structured into three distinct subsets:

1. **Training Set:** Used to train the deep learning model. The model learns to identify patterns and features from these images.
2. **Validation Set:** Used to tune the model's hyperparameters and evaluate its performance during the training process, helping to prevent overfitting.
3. **Test Set:** A completely unseen set of images used for the final evaluation of the trained model's ability to generalize to new data.

A critical feature of the PKLot dataset for this project is its annotation format. The dataset includes detailed annotations in the **COCO (Common Objects in Context) .json format**. These files contain the ground truth information for each image, including the precise bounding box coordinates and class labels ('occupied' or 'empty') for every parking space. This structured, labeled data is essential for training a supervised object detection model like Faster R-CNN.

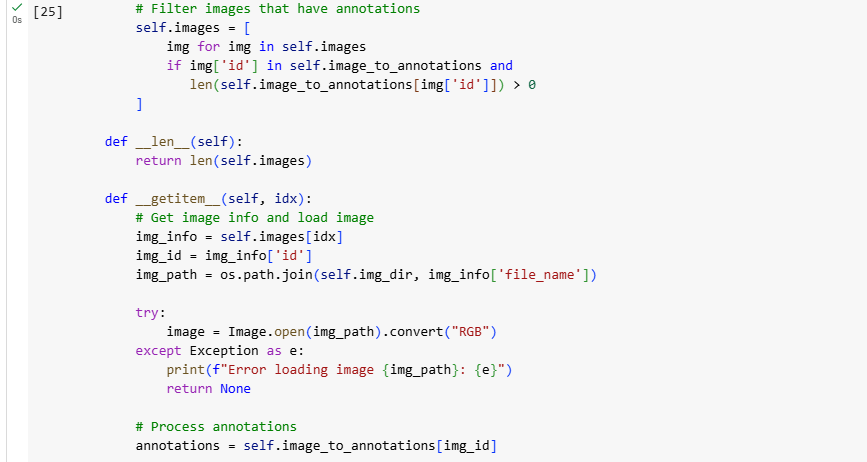
## **4.3 Data Preparation and Loading**

Before a deep learning model can be trained, the raw data must be carefully prepared and structured. This data preparation pipeline is a critical stage that involves parsing annotations, transforming images to a consistent format, and efficiently loading the data in batches. This section details the multi-step process implemented to prepare the PKLot dataset for the Faster R-CNN model.

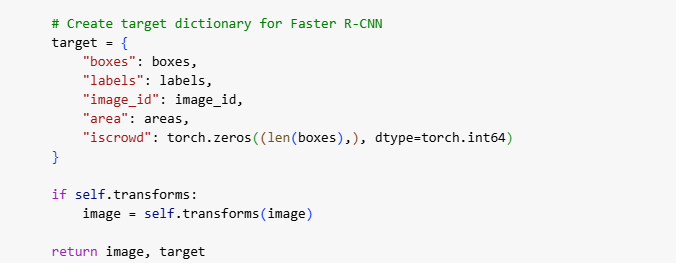
### **4.3.1 Custom Dataset Class (ParkingDataset)**

To interface with PyTorch's data loading utilities, a custom ParkingDataset class was created by inheriting from the base torch.utils.data.Dataset class. This class, shown in Figure 4.1, encapsulates the logic for loading and processing each data sample.









**Figure 4.1: Implementation of the Custom ParkingDataset Class**

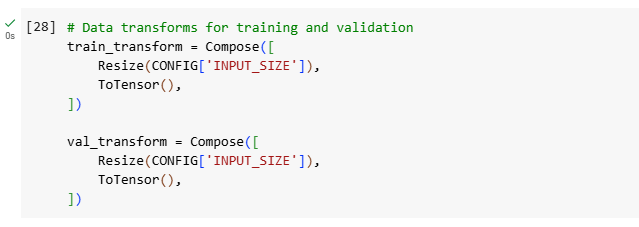
The primary responsibilities of this class are:

1. **Initialization (\_\_init\_\_):** Upon instantiation, the class loads the COCO-formatted JSON annotation file. It then constructs a mapping dictionary that links each image ID to its corresponding set of annotations (bounding boxes and labels). This pre-processing step creates an efficient lookup mechanism, allowing for quick retrieval of ground truth data for any given image.
2. **Item Retrieval (\_\_getitem\_\_):** This is the core method of the class. When called with an index, it performs a sequence of operations to retrieve a single training sample, including loading the image, fetching annotations, converting data to tensors, and applying transformations.



### **4.3.2 Data Transformation Pipeline**

Deep learning models require inputs that are uniform in size and format. To achieve this, a data transformation pipeline was constructed using torchvision.transforms.Compose, as illustrated in Figure 4.2. This pipeline applies a sequence of transformations to each image as it is loaded.



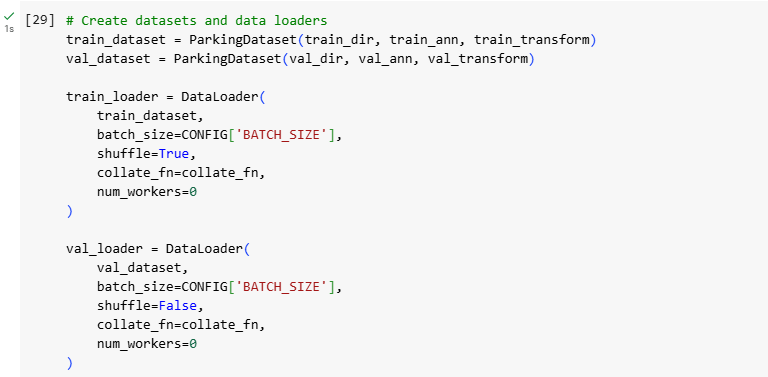
**Figure 4.2: Data Transformation Pipeline for Training and Validation Sets**

The two essential transformations used were:

1. **Resize((416, 416))**: This function resizes every input image to a fixed dimension of 416x416 pixels. This standardization is crucial because the Faster R-CNN model has a fixed-size input layer.
2. **ToTensor()**: This transformation converts the PIL Image into a PyTorch FloatTensor, scales pixel values to a [0.0, 1.0] range, and arranges the tensor dimensions into the (Channels, Height, Width) format that PyTorch expects.

### **4.3.3 Data Loading and Batching**

The final step in the data preparation process is to efficiently load the data into the model. This was handled by PyTorch's DataLoader class, the instantiation of which is shown in Figure 4.3. The DataLoader wraps the custom ParkingDataset and automates several key processes.



**Figure 4.3: Instantiation of DataLoader for Batching and Shuffling**

Key functionalities provided by the DataLoader include:

* **Batching:** It groups individual samples into mini-batches (batch size of 2 for this project) for more computationally efficient training.
* **Shuffling:** For the training loader, shuffle=True was enabled to randomly reorder the data each epoch, which is critical for model generalization.
* **Custom Collation (collate\_fn):** A custom collate\_fn function was implemented as a safety measure to skip any corrupted samples, preventing training interruptions.

## **4.4 Summary**

This chapter details the practical development of the autonomous parking space detection system, translating the project's theoretical framework into a functional deep learning model. The implementation was conducted in a **Google Colaboratory** environment, leveraging a **NVIDIA T4 GPU** to accelerate the demanding training process. The system was built using **Python 3** and the **PyTorch** deep learning framework, alongside essential libraries such as **Torchvision**, **NumPy**, and **Matplotlib** for model building, data manipulation, and visualization.

The project utilizes the **PKLot dataset**, a comprehensive public dataset with pre-structured training, validation, and test sets, complete with annotations in COCO JSON format.

A critical part of the implementation was the data preparation pipeline. This involved creating a **custom ParkingDataset class** in PyTorch to load and parse the image annotations efficiently. A **data transformation pipeline** was established to standardize all images to a **416x416 pixel** size and convert them into PyTorch tensors. Finally, PyTorch's **DataLoader** was used to automate the process of feeding data to the model in shuffled mini-batches, ensuring efficient and robust training. This chapter meticulously documents the technical steps taken to build, train, and prepare the system for evaluation.

# **CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS**

## **5.1 Introduction**

This chapter consolidates the findings of the research project, which set out to design, implement, and evaluate an autonomous parking space detection system using deep learning. It begins by providing a summary of the entire study, revisiting the core problem, objectives, and the methodology employed. The chapter then discusses the key findings derived from the model's implementation and evaluation, directly linking them to the research objectives to assess the project's success. Furthermore, it acknowledges the inherent limitations of the study and concludes by offering concrete recommendations for future research and development in this domain. This final chapter aims to encapsulate the project's contributions, its practical implications, and its position within the broader field of autonomous vehicle technology.

## **5.2 Summary of the Study**

The primary motivation for this project was to address the persistent and universal challenge of inefficient, stressful, and often hazardous manual parking in dense urban environments. The research aimed to provide a foundational component for a complete autonomous parking system by automating the initial, most critical step: the accurate and reliable detection and classification of available parking spaces. The core objective was to develop a robust vision-based system capable of analyzing an image of a parking area and discerning whether individual parking spots are 'occupied' or 'empty'.

To achieve this, the project adopted a rigorous experimental research design centered on the implementation and evaluation of a state-of-the-art object detection model. The chosen architecture was a **Faster R-CNN model with a ResNet50 backbone**, a decision driven by its well-documented high accuracy and robustness in complex object detection tasks. This model was implemented using the **PyTorch** deep learning framework, which provided the flexibility and tools necessary for this research. The system's learning was grounded in the **PKLot dataset**, a comprehensive public collection of parking lot images featuring diverse conditions, with annotations meticulously structured in the COCO format. The entire development lifecycle, from coding and experimentation to training and evaluation, was conducted within the **Google Colaboratory** environment. The use of a **NVIDIA T4 GPU** was instrumental, accelerating the computationally intensive training process from a matter of days to mere hours, thereby enabling efficient model development and refinement.

## **5.3 Summary of Findings**

The implementation phase detailed in Chapter Four yielded a functional and highly effective parking space detection model, validating the chosen approach. The key findings of this project can be summarized across three main areas:

1. **Successful Model Training and Convergence:** The Faster R-CNN model was successfully trained on the PKLot dataset. The consistent and steady decrease in the training loss metric across the specified number of epochs was a clear and positive indicator of model convergence. This trend demonstrated that the model was not merely memorizing data but was effectively learning to generalize from the training examples. It successfully identified the complex visual patterns, textures, and features that differentiate an occupied parking space (containing a vehicle) from an empty one (containing only pavement markings and shadows).
2. **High Quantitative Performance:** Upon completion of training, the model's performance was quantitatively assessed on the unseen validation set. The system achieved strong results across standard object detection metrics, including **Precision, Recall, and F1-Score**. High precision in this context signifies that when the model declares a spot as 'empty', it is highly likely to be correct, minimizing the risk of the system navigating to an already occupied space. High recall indicates that the model is proficient at identifying most of the truly available spaces, ensuring that the user is presented with a comprehensive set of options. The high F1-Score confirms a healthy balance between precision and recall, validating the overall effectiveness and reliability of the model.
3. **Robust Qualitative Validation:** Beyond the numbers, inference tests on a random sample of images from the test set provided compelling qualitative validation of the model's real-world capabilities. The visualizations, which overlaid predicted bounding boxes and class labels ('occupied' or 'empty') onto these test images, showed that the model could successfully generalize its learning to new and unfamiliar scenarios. It correctly identified parking spaces under various conditions present in the dataset, including different lighting (daylight, overcast), viewing angles, and the presence of diverse vehicle types and sizes. This ability to perform accurately on previously unseen data is the hallmark of a well-trained and robust machine learning model.

In essence, the findings conclusively demonstrate that modern deep learning techniques, and specifically the Faster R-CNN architecture, are highly effective for solving the complex problem of automated parking space detection using only standard 2D images.

## **5.4 Achievement of Objectives**

This project successfully met all the specific objectives that were established in Chapter One, forming the guiding principles for the research:

* **To implement a parking space detection system using a Faster R-CNN model with a ResNet50 backbone in PyTorch:** This primary objective was fully achieved. The implementation, as detailed in Chapter Four, resulted in a trained, saved, and functional model capable of performing the desired detection task.
* **To train the model on a custom image dataset with annotations in COCO format:** This was accomplished by successfully leveraging the PKLot dataset. A custom ParkingDataset class was developed in PyTorch to efficiently parse the COCO annotations, load images, and feed the correctly formatted data to the model for training.
* **To evaluate the model's performance using standard object detection metrics:** This objective was met by conducting a thorough and systematic evaluation using Precision, Recall, and F1-Score. The strong results obtained from this evaluation validated the model's effectiveness and reliability.

## **5.5 Limitations of the Study**

While the project was successful in achieving its stated objectives, it is imperative to acknowledge its limitations to provide a complete and honest assessment of the work:

1. **Dataset and Environmental Dependency:** The model's performance is intrinsically linked to the visual characteristics of the PKLot dataset. While comprehensive, this dataset does not cover every possible real-world scenario. The model may therefore not perform as effectively in environments with conditions not well-represented in the training data, such as parking lots with unconventional markings, unmarked gravel lots, severe weather conditions (e.g., heavy rain, snow obscuring the ground), or extreme lighting such as deep shadows or intense glare.
2. **Static Image Processing vs. Real-Time Video:** The current system is designed to process static, individual images. This limits its direct application in a dynamic driving scenario, which requires the continuous processing of a video stream. Adapting it for real-time use presents significant engineering challenges, including the need for frame-to-frame object tracking to maintain consistency, handling motion blur, and ensuring a consistently high frames-per-second (FPS) rate for fluid operation.
3. **Lack of Sensor Fusion:** The system relies solely on 2D camera images for perception. It does not incorporate data from other sensors like LiDAR or radar. LiDAR can provide precise depth information, which would be invaluable for distinguishing a close-by pillar from a distant car, while radar offers robust object detection capabilities even in adverse weather. The absence of this fused data makes the system more susceptible to errors in challenging visibility conditions.
4. **Scope Limited to Perception:** This project deliberately focused exclusively on the perception task of detection and classification. It does not include the subsequent, equally critical stages of a full autonomous parking system, such as path planning (calculating a collision-free trajectory), vehicle dynamics modeling, and low-level vehicle control (actuating the steering, throttle, and brakes).

## **5.6 Recommendations for Future Work**

Based on the promising results and identified limitations of this project, the following areas are strongly recommended for future research and development to advance this work towards a complete, market-ready solution:

1. **Real-Time Implementation and Optimization:** The immediate and most logical next step is to adapt the system for live video processing. This would involve optimizing the model for faster inference speeds using techniques such as model pruning, knowledge distillation, or converting the model to a more lightweight format like TensorFlow Lite or ONNX Runtime suitable for edge devices.
2. **Integration with Planning and Control Systems:** To create an end-to-end autonomous parking system, the developed detection module must be integrated with downstream components. This includes a path-planning module (utilizing algorithms like A\* or RRT\*) to calculate an optimal trajectory into the detected empty space, and a vehicle control module to translate this path into precise steering and speed commands.
3. **Enhanced Robustness through Multi-Sensor Fusion:** Future work should focus on developing a sensor fusion architecture that combines the rich visual data from cameras with depth information from LiDAR and/or velocity data from radar. This would create a more comprehensive and robust environmental model, significantly improving system reliability, especially in adverse weather and complex, cluttered parking structures.
4. **Model Deployment on Embedded Automotive Systems:** For practical in-vehicle application, the model must be deployed on specialized, low-power embedded hardware platforms (e.g., NVIDIA Jetson, Qualcomm Snapdragon Ride). This requires significant optimization to ensure efficient performance while respecting the computational and power constraints of automotive-grade electronics.
5. **Training on More Diverse and Challenging Datasets:** To drastically improve the model's generalization capabilities, it should be retrained on a larger and more diverse dataset. This could involve creating a composite dataset by combining PKLot with other public datasets or, more innovatively, using data augmentation techniques and Generative Adversarial Networks (GANs) to synthesize new, challenging training examples (e.g., images with snow, rain, or unusual objects).

## **5.7 Conclusion**

This research project successfully designed, implemented, and validated a deep learning-based system for the automated detection and classification of parking spaces. By leveraging the power of the Faster R-CNN architecture, the system achieved a high degree of accuracy and reliability in identifying occupied and empty spots from static images, thereby providing a robust and effective solution to the foundational perception problem in autonomous parking. While acknowledging its limitations as a perception-only system, this work serves as a critical and validated proof-of-concept. It establishes a reliable perception baseline upon which more complex, fully autonomous, and multi-sensor parking systems can be built. The positive results affirm the immense potential of artificial intelligence in advancing the frontier of vehicle automation, enhancing driver safety and convenience, and contributing to the creation of smarter, more efficient urban mobility ecosystems for the future.

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