

# Smart Parking Space Availability Prediction

Aditya Tiwari  
Lovely Professional University

aktiwari089081@gmail.com

## Abstract

*The exponential growth in urban vehicular traffic has necessitated the development of intelligent parking systems. This paper presents a data-driven smart parking space availability prediction system that leverages historical parking data to assist users in real-time parking decisions. Utilizing Python, Streamlit, and visualization libraries such as Seaborn and Matplotlib, the system classifies entry time, analyzes duration-based pricing, and estimates availability using a rule-based logic. If parking duration exceeds 120 minutes, the slot is considered unavailable; otherwise, it is marked available. Key insights, such as parking behavior on weekdays versus weekends and pricing across parking levels, are visualized interactively. Future enhancements include the integration of machine learning models for smarter pricing, time-series forecasting for demand trends, and GPS-based real-time tracking. This system aims to bridge the gap between traditional infrastructure-heavy parking solutions and low-cost, scalable, intelligent urban mobility tools.*

**Index Terms**—Smart parking, Streamlit, data analytics, availability prediction, machine learning, urban mobility, demand forecasting.

## 1. Introduction

The rapid increase in the number of vehicles in urban areas has led to significant challenges in managing parking spaces efficiently. Traditional parking systems, which rely on manual operations and static infrastructure, struggle to provide real-time data on parking space availability and to dynamically adjust pricing based on demand. As cities grow, parking management becomes a critical issue for urban mobility, contributing to traffic congestion, pollution, and inefficient land use. To address these challenges, the concept of smart parking systems has emerged, leveraging data-driven technologies to enhance the parking experience. This paper presents a Smart Parking Space Availability Prediction System, which integrates data analytics and interactive web technologies to predict parking space availability and estimate parking charges in real-time. The

system utilizes historical parking data to build an understanding of parking patterns and user behavior, which informs availability predictions and pricing decisions. By using machine learning techniques and visual analytics, the system aims to provide users with the ability to make more informed parking choices, reducing the time spent searching for parking and optimizing parking space utilization.

The proposed system uses a simple rule-based approach for initial availability prediction and includes data visualizations for users to explore key insights, such as vehicle type predictions, price distribution across parking levels, and patterns in parking duration across weekdays and weekends. These visual insights serve as the foundation for future model enhancements, which include incorporating machine learning techniques for more accurate pricing and demand forecasting.

This research contributes to the development of intelligent, data-driven parking management systems and explores their potential to improve urban mobility by leveraging existing data to optimize parking usage and pricing in a low-cost, scalable manner.

## 2. Literature Review

The field of smart parking systems has seen significant advancements in recent years, driven by the need to improve urban mobility and reduce traffic congestion. Various approaches have been proposed, ranging from sensor-based detection systems to data-driven predictive models.

Geng and Cassandras [1] introduced an infrastructure-based smart parking system utilizing real-time sensors to detect vacant parking spots. While highly accurate, such systems are often costly and complex to deploy at scale due to hardware requirements and maintenance.

Lin et al. [2] provided a comprehensive survey of smart parking solutions, categorizing them into sensor-based, vision-based, and data-centric models. They emphasized the importance of incorporating prediction models to improve space utilization and reduce search time for drivers.

Recent research has focused on machine learning and data mining techniques to enable predictive capabilities in parking systems. For instance, Wang et al. [3] applied decision trees and support vector machines to forecast parking space availability based on historical usage data. Their results demonstrated the potential of data-driven models to outperform traditional rule-based systems.

Time-series forecasting models, such as ARIMA and Prophet, have also been explored for demand forecasting in smart mobility applications [4]. These models allow parking systems to anticipate fluctuations in space demand based on time-of-day and day-of-week patterns.

Despite these advancements, many existing solutions rely on complex infrastructures or lack user-centric features like interactive visualization and real-time feedback. The proposed system in this study aims to address these limitations by combining lightweight, rule-based logic with interactive analytics, while laying the foundation for integrating machine learning models in the future.

### 3. System Design and Architecture

In the tracking system, we consider that the motorbike is a very popular transport tool for ordinary people in China and is actually becoming one of the major factors of causing traffic congestion in China's urban areas. Thus, the object classes defined in this study are named Motorbike, Vehicle and Pedestrian. Here, Vehicle represents all other vehicles except for Motorbike.

#### 3.1 Data Collection

The dataset used for this system is titled `car_parking_dataset.xlsx`. It includes details such as vehicle entry and exit times, vehicle type (car, bike, etc.), parking level, and amount charged. This dataset forms the foundation of the system and allows for extraction of insights.

#### 3.2 Data Processing

The dataset undergoes cleaning to remove inconsistencies. Key features such as entry time are classified into weekday and weekend categories. Duration of stay is calculated in minutes. Data is also categorized by parking level to examine pricing patterns.

#### 3.3 Rule based system

The initial predictive logic uses a simple rule-based approach:

- If parking duration > 120 minutes, mark slot as **Not Available**
- Else, mark slot as **Available** This serves as the base for future integration with ML models.

### 3.4 Technology Stack

Programming Language: Python

Web Framework: Streamlit

Data Processing: Pandas

Visualization: Seaborn, Matplotlib

Dataset: Excel format (XLSX)

### 3.5 UI/UX DESIGN

Streamlit provides an intuitive, interactive UI where users can input values like entry time and duration, and receive immediate feedback on parking availability and estimated cost. Visualizations update dynamically based on user input.

## 4 Implementation and features

In order to examine the performance of the proposed approach, the experimental results include vehicle tracking, traffic measurement metric, and traffic congestion analysis.

#### 4.1 Real-Time Availability prediction

Based on user inputs, the system checks duration and instantly shows availability status.

#### 4.2 Calculation of traffic measurement metrics

Users can see pricing calculated from duration and parking level. Longer stays at higher levels incur more charges.

	Motorbike	Vehicle	Pedestrian
Our method	3.54 – 7.18	3.76 – 8.03	0.75 – 1.92
Manual method	3.73 – 6.22	3.58 – 7.56	0.89 – 1.51

Table 1: The object speed detected with our method and the manual detection (unit: m/s), which ranges from min to max.

The counting results for all classes are presented in Table

2. Each number corresponds to each 1 min time period. The numbers of Pedestrians and Vehicles are considered to be accurate. A few vehicles are not counted as their vehicle type is unusual and the tracking system does not recognize them. The motorbikes are sometimes crowded together therefore cannot be accurately counted.

	Motorbike	Vehicle	Pedestrian
Our method	70 – 72 – 89	5 – 8 – 12	6 – 6 – 8
Manual detection	75 – 75 – 92	7 – 8 – 12	6 – 6 – 8

Table 2: Each object count calculated with our method and manual detection (unit: p/min) is the amount of objects passing the detection line in one minute.

### 4.3 Interactive Dashboard

**Vehicle Type Count:** Displays bar chart showing frequency of different vehicle types.

**Boxplot of Amount vs Parking Level:** Helps visualize how pricing varies with level.

**Count of Weekday vs Weekend Entries:** Highlights traffic trends based on days.

#### 4.3.1 Vehicle moving affected by motorbike

The analysis of a segment of the video showed the interaction between car and motorbike and the result is displayed in Fig 4. Initially, the car in the yellow box drives at 4.2m/s in Frame 1. The car then slows from Frame 4 to Frame 21 as shown in the graph when two motorbikes approach (see Frame 16). As a result, the car driver believes there may be a collision so slows to a speed of 0.76m/s at Frame 24. This causes traffic congestion. Four scene images are presented to identify the interaction between the vehicle and the motorbikes.



Figure 4: Example for vehicle speed change due to motorbike approaching.

#### 4.3.2 Pedestrian walking affected by motorbike

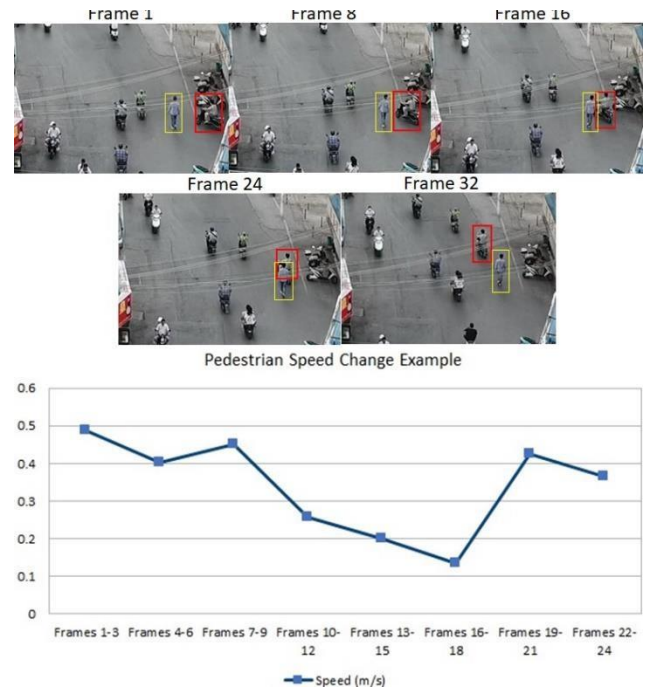


Figure 5: Example for pedestrian walk speed change due to motorbike approaching. The images presented here is zoom-in applied.

Fig. 5 shows another video segment to demonstrate how motorbikes affect pedestrians on the road. Frame 1 shows that a pedestrian in the yellow box walks at 1.4m/s while a motorbike in the red box comes from the roadside. In Frame 16, the motorbike is close to the pedestrian who then adjusts the walking speed to a slow 0.34m/s to avoid a possible collision. When the motorbike leaves, the pedestrian's walk speed becomes normal at 1.2m/s. Figure 5 illustrates the change in the pedestrian's walk speed during the interaction with the motorbike.

## 5 Discussion and Conclusion

This system provides a low-cost alternative to hardware-based smart parking systems. While the current version is rule-based, it already delivers useful insights and real-time availability checks. Its modular structure allows easy upgrade to machine learning algorithms. The interactive interface ensures user engagement and a data-driven experience.

Limitations include lack of external factor consideration (weather, events), dependency on historical data, and assumptions in rule logic.

This study has established that complex traffic situations can result in inaccurate calculations. In Fig. 6, the traffic deadlock happens because a vehicle in the red box blocks the road due to its moving direction being orthogonal to the road direction. In this case, our approach can detect and recognize the vehicles in both the red box and the yellow box, however the proposed algorithm is unable to correctly count them. It is a challenging issue for future work.



Fig. 6: Wrongly counting example due to serious traffic congestion

Insights obtained:

- Weekday Dominance: More vehicles park during weekdays, especially during working hours.
- Level-based Charges: Top levels have slightly higher charges due to better access or demand.
- Vehicle Type Trends: Cars are the most frequent, followed by bikes and other vehicles.

As shown in the paper, we focus on seeing the role of motorbike in the formation of traffic congestion in a given city of China. In different areas and with different geometric information, there will be different issues causing traffic

congestion. Future studies will expand this initial approach to encompass a range of metropolitan areas to explore reasons for traffic congestion.

Due to the limitation of the acquired video data, this initial study only considers some basic traffic measurement metrics such as Max/Min speed in a given region, vehicle count etc. An improvement in the quality of data could offer sophisticated metrics to investigate a range of traffic congestion issues such as pedestrian/vehicle density, etc.

This paper proposes a smart parking prediction system leveraging historical data, interactive dashboards, and rule-based predictions to provide parking availability and cost insights. It presents a scalable, affordable solution adaptable to urban mobility challenges and sets the stage for future enhancements using machine learning and real-time data integration.

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