# EfficientDet-Based Event Detection for Smart Parking System using Ontology and SPARQL Query

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**Abstract.** Currently, the dynamic nature of traffic management demands mobile surveillance capabilities, which are practical for the integration of 5G networks and edge computing advancements. The advancement of Multi-access Edge Computing (MEC) has enabled data processing closer to the source, significantly reducing latency and enhancing responsiveness. Cities require dynamic and difficult monitoring strategies to identify illegally parked vehicles effectively. Mobile surveillance is effectively carried out using platforms such as Unmanned Aerial Vehicles (UAVs) or ground vehicles, which gather multimodal data and transmit it to the closest edge server through a 5G connection for rapid processing. The edge server transmits actionable insights to the control unit with minimal delay, allowing an effective arrangement of real-time reduction strategies. Vehicles equipped with cameras and sensors traverse urban areas, capture roadside data, and transmit it to nearby edge servers through a 5G network for real-time analysis. EfficientDet is employed as the main object detection model to accurately localize vehicles within the video frames. Ontology-based reasoning permits surveillance data and facilitates the construction of knowledge graphs. Semantic queries are stated using SPARQL, and Description Logics (DL) allows recapture information without the need to store full video sequences. The proposed EfficientDet-Based Smart Parking System provides a better accuracy of 98.4% than the existing Onto-ViBeNet (Ontology-enhanced Vehicle Behavior Prediction with YOLOv5s).

## 1 Introduction

The number of vehicles is continuously increasing, affecting parking spaces and significantly affecting the development and dynamics of the city's parking industry [1]. Airports are evolving into smarter, more efficient centers, where inventions such as automated baggage handling and smart parking reshape the travel experience [2]. Smart Parking (SP) helps reduce search time by providing drivers with live updates on available spots through their mobile devices [3]. As roadside traffic continues to grow rapidly, drivers face growing challenges in identifying available outdoor parking spaces [4]. Cloud-centric parking management provides a solution to heterogeneous systems but is not suitable for environments with incompatible stakeholder goals, such as competitive parking markets, where revenue maximization drives individual decision-making [5]. Many cities depend on free on-street parking to compensate for limited paid parking options. However, the demand for cost-conscious drivers results in an excessive number of parked vehicles, thereby worsening traffic congestion [6]. In high-density environments such as university campuses, effective parking management is hindered by frequent violations, including unauthorized parking, time overruns in regulated areas, and the use of restricted zones [7]. By rearranging space allocation, SP systems not only increase profitability for operators but also improve user satisfaction and urban traffic pressure [8]. Data-driven methods, particularly Machine Learning (ML) and Deep Learning (DL), are highly effective in adapting to dynamic environments owing to their inherent flexibility and responsiveness [9]. Although SP(SP) systems offer considerable advantages, adoption remains limited because a significant gap in understanding user intentions leads to hesitation among potential users when faced with unaware technologies [10]. Maria Assunta Cappelli and Giovanna Di Marzo Serugendo [11] developed a method for building ontologies using a Large Language Model (LLM). ChatGPT-4o was used to develop an ontology that focuses on user preferences for adaptive vehicle interfaces. The developed method follows a standard sequence by defining the domain, extracting terms, constructing class hierarchies, specifying properties, formalizing the ontology, populating it, and validating its integrity. Human error was important to the workflow, providing continuous improvement of terminology, disambiguation of concepts, and validation

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of the generated content. Validation confirmed the ontologies' consistency, semantic accuracy, and inferential strength with SPARQL queries, demonstrating their reasoning performance. However, when sensitive data such as biometrics are included, the ontology does not clearly ensure privacy safeguards (e.g., encryption and GDPR compliance) or legal constraints, which was important in domains such as autonomous vehicles. Antonios Pliatsios et al. [12] introduced S2NetM (Social Network of Things Middleware) to enhance semantic interoperability and collaborative intelligence in Social Internet of Things (SIoT) environments. S2NetM integrates multiple components such as Context Management, Owner Control, User Profiling, Service Discovery, Trustworthiness Management, Friendship Selection, Relationship Management, and Semantic Engines to enable dynamic, context-aware interactions among heterogeneous IoT entities. S2NetM involves the semantic annotation of data, ontology alignment, and reasoning mechanisms that allow devices to form social relationships and collaborate effectively. The middleware was evaluated through a real-world usage called the Green Route, which demonstrated the capability to generate eco-friendly travel recommendations by leveraging semantic relationships among IoT sensors, open data platforms, and user preferences. However, S2NetM lacks integration with edge computing for real-time responsiveness, whereas the ontology arrangement process was conceptually robust, where performance under large-scale heterogeneous deployments remains unverified. Xiaolong Xu et al. [13] employed the YOLOv5s model with ontology reasoning to enhance accessibility and reliability in autonomous driving systems. The YOLOv5s model is combined with the Convolutional Block Attention Module (CBAM) and a weighted Bi-directional Feature Pyramid Network (BIFPN) to detect the brake light status under various lighting and obstruction conditions. The visual inputs were fed into an ontology model that encoded traffic rules, vehicle types, lane positions, and light signals to achieve future vehicle exercises, such as turning, slowing down, or stopping. However, the employed method showed improved accuracy and accessibility compared to traditional black box models, yet still faced challenges where the ontology lacks dynamic adaptability to real-time changes. The data properties are minimally limited to vehicle ID and type, restricting the model's capability to represent motion characteristics, such as speed or acceleration. Ashish Singh Patel et al. [14] introduced a method for real-time traffic monitoring through mobile surveillance in Intelligent Transport Systems (ITS). The process includes 5G infrastructure and Multi-access Edge Computing (MEC) to process multimodal data video, GPS, and speed from mobile vehicles, such as Smart Bike Sharing Systems (SBSS). The development of ipark ontology, which integrates structured sensor data and unstructured video, feeds into a machine-readable RDF format, enabling semantic reasoning and efficient storage. For object detection, YOLOv3 was used for vehicle tracking, lane detection, and Automatic Number Plate Recognition (ANPR), followed by reasoning through SWRL rules, querying via SPARQL and Description Logic to identify illegally parked vehicles. However, the introduced method performs better with semantic integration and rule-based reasoning and still faces difficulty in accurately estimating the vehicle length when the object is partially visible or distant from the camera. Amy J.C. Trappey et al. [15] introduced an ontology-based patent analysis method specifically for bike-sharing systems to identify competitive advantages in product-service business models. The proposed method integrates domain ontology construction, keyword extraction, K-means clustering, and Technology Function Matrix (TFM) analysis to map the technological landscape of bike-sharing innovations. The process begins by building a hierarchical ontology plan that categorizes patents into four subdomains: parts and structure, information processing, bicycle anti-theft, and e-business. However, the introduced method lacks real-time adaptability and didn't incorporate dynamic usage data or behavioral analytics, which is crucial for optimizing user experience and operational efficiency in live bike-sharing environments.

The contribution of the proposed EfficientDet-Based Smart Parking System is as follows:

- The system introduces a SmartPark ontology that organizes sensor and visual data into RDF format, enabling rule-based reasoning through SWRL and SPARQL which is for context-aware identification of complex parking violations without storing full video footage.
- By deploying EfficientDet on mobile surveillance units equipped with dual cameras and edge processors, the system achieves a high detection accuracy with minimal latency, making it suitable for dynamic urban environments.
- The integration of 5G connectivity and Multi-access Edge Computing (MEC) enables real-time processing and transmission of marked metadata instead of raw video, ensuring scalability and privacy compliance in smart-city deployments.

In this paper, Section 2 describes the problem statement, which is solved in Section 3 of the proposed method, and Section 4 and 5 discuss the experimental results and conclusions.

## 2 Problem Statement

Illegal parking in urban areas remains difficult to monitor to limited manpower and static implementation systems. The existing methods lack mobility, semantic understanding, and real-time responsiveness. The proposed system uses EfficientDet with Smart Park ontology and SPARQL queries to detect violations contextually, which enables mobile edge-based surveillance that is scalable and privacy-aware.

## 3 Proposed Method

In the proposed method, real-time video data are captured using a dual-camera setup mounted on a mobile surveillance unit. The front-facing camera

recorded vehicular movement and number of plates, while the side-facing camera monitored roadside activity for potential parking violations, as shown in Figure 1. Each video stream is processed on a device and transmitted through a 5G network to a Multi-access Edge Computing (MEC) node. Frames are sampled at regular intervals to extract relevant features such as vehicle type, location coordinates, motion status, and lane position. The live feed enabled continuous monitoring and semantic annotation without storing full video footage, thereby ensuring both efficiency and privacy.

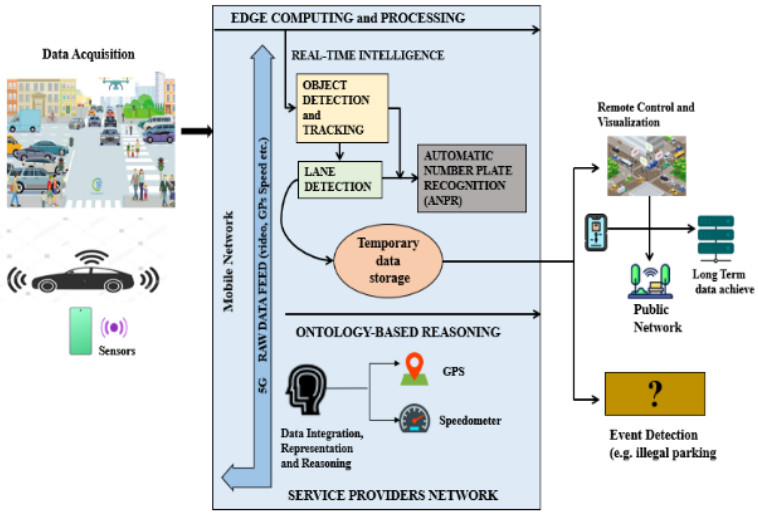


**Fig. 1.** Overall architecture of proposed EfficientDet-based smart parking system.

### 3.1 Information Extraction

Objects in the image are identified along with bounding boxes, movement paths, lane markings, and vehicle registration numbers. Detection occurs in real-time using a DL model that locates objects and draws boxes around them. Tracking data are collected and linked to each object to determine whether a vehicle is moving or stationary. Every object receives a unique ID and the length of its movement path is measured. For variable footage, a tracking method based on a Siamese network improves accuracy. Lane markings are analyzed to determine whether a parked vehicle is positioned correctly. To determine whether a vehicle is within the designated driving area, its bounding box is compared with the pixel coordinates of the detected lane. Lane boundaries are identified by first applying blur to reduce noise, followed by edge detection techniques to emphasize the horizontal and vertical lane markers. The region of interest is defined as the roadside area, focusing specifically on the portion of the lane visible behind the camera. A line-detection algorithm is then used to trace the complete lane structure within the image. For vehicle identification, the system locates the license plate by detecting distinct contours from the front image of the car. Once the plate is isolated, alphanumeric characters are extracted using optical character recognition (OCR) tools.

### 3.2 Smart park ontology

The Smart Park ontology is developed to systematically manage surveillance data gathered from various sensors, including cameras, GPS units, and speedometers, along with information related to vehicle trips. This trip data captures the movement of mobile vehicles and documents key metrics, such as departure and arrival times, total travel duration, and distance traveled. Data collection is facilitated using smartphones equipped with integrated sensors and cameras. To ensure broad compatibility and scalability, the system is designed to interface seamlessly with smart bike-sharing platforms, making it adaptable to different types of mobile vehicles. The ontology itself is structured around a set of classes, object properties that define the relationships between classes, and data properties that store specific attributes for each class. The core of this ontology is the SmartBikeSystem class, which encompasses both bike-specific and sensor-derived data. Sensor inputs included location coordinates from the GPS, speed readings, and visual data from the cameras. The Camera class is linked to the vehicle class, which is further divided into categories such as cars, buses, vans, motorbikes, and jeeps. Another key component of SmartBikeSystem is the BikeSharing class, which maintains records of trips and station locations. The data properties defined within a Smart Park play a crucial role in identifying instances of unauthorized parking and offer valuable insights into roadside conditions. This structured framework supports the development of a dynamic knowledge base that can be routinely updated and leveraged for traffic analyses, enforcement, and urban infrastructure planning.

### 3.3 Information representation

Data gathered from surveillance tools such as video cameras, GPS devices, and speedometers are structured using the Resource Description Framework (RDF) to enable streamlined data access and logical analysis. Each vehicle captured in the footage s assigned a distinct tracking identifier, with visual information documented at the level of individual tracks. The tracks are treated as individuals within the ontology, and their characteristics are stored as data properties; each individual represents

a vehicle's movement, and its track data are matched with sensor readings using timestamps. The visual data included the vehicle's position, shape, size, and movement path. Objects and their bounding boxes are identified using advanced detection methods, and tracking algorithms connect these detections across frames to build continuous tracks in real-time. Lane markings on the roadside re detected using edge detection techniques and linked to each vehicle track within the ontology. Sensor readings, such as GPS coordinates and speed combined with video data using matching timestamps. Speed helps to determine if a vehicle is in motion, whereas GPS data pinpoint its location when parked. The collected data maintained as attributes linked to individual entities within the ontology, enabling the system to detect unauthorized parking and contribute to comprehensive traffic monitoring and analysis.

#### *3.3.1 Vehicle detection through EfficientDet*

EfficientDet is a highly advanced object-detection architecture developed by Google Brain in 2020. It builds upon the EfficientNet family of convolutional neural networks (CNNs), which are known for their ability to deliver strong performance with minimal computational cost. EfficientDet uses compound scaling, a technique that simultaneously increases the depth, width, and resolution of the network in a balanced manner. This allows the model to maintain high accuracy while remaining efficient across a wide range of resource constraints from lightweight devices to high-performance systems. The architecture includes several key components: The EfficientNet backbone for feature extraction, a Bidirectional Feature Pyramid Network (BiFPN) for effective multi-scale feature fusion, convolutional blocks, and dedicated heads for classification and regression tasks. Anchor boxes are also used to detect objects of various sizes and shapes. Together, these elements make EfficientDet a powerful and scalable solution for real-time object detection, which is particularly useful in applications such as UAV-based surveillance where accuracy and speed are critical.

### 3.4 Detection of illegally parked vehicles

Illegally parked vehicles are detected by evaluating the structured data stored within an ontology framework. These data is sourced from mobile surveillance units equipped with cameras and sensors, including GPS and speedometers, as well as vehicle movement logs, lane boundary information, and license plate identification systems. To judge the parking status, the system compares the lane coordinates with the lower central edge of each vehicle. If the lane is visible above the vehicle, it is considered correctly parked. In contrast, if no lane is detected and the vehicle remains stationary, the location is flagged as a restricted zone and the vehicle is classified as improperly parked. To identify such violations, the system employed rule-based reasoning and structured query techniques. These methods allow for the integration of visual and sensor data with predefined logical rules, thereby enabling the detection of complex parking infractions. Vehicle identification is handled by an Automatic Number Plate Recognition (ANPR) module, which uses image processing methods such as segmentation to isolate the license plate and contour detection to define its boundaries. Once the plate is extracted, its contours are adjusted based on the expected character dimensions and placement. The final step involves reading the registration number using the Tesseract 4 OCR, a widely recognized optical character recognition engine known for its precision in extracting text from images.

#### *3.4.1 Semantic Web Rule Language (SWRL) based reasoning*

Rules are created to reason over the data and generate OWL axioms, where rules help find relationships between different classes using logic-based reasoning. One rule compares the time taken by a vehicle to move with the time required to pass a stationary vehicle. Based on this comparison, the system identifies whether the vehicle is moving or stationary. Two specific relationships are defined: one for stationary vehicles and one for moving vehicles.

Vehicle stationary: The vehicle stationary property is used to establish a relationship between two classes when a vehicle appears to be stationary based on a comparison of two time values. The first value represents the time it takes for the vehicle to pass through the camera's field of view, calculated from the total number of frames in the vehicle's track and the frame rate of the video. The second value estimates the time required to traverse the actual physical length of the vehicle, which depends on the type of vehicle and speed of the moving camera. To compute the first-time value, the system uses the formula involving $L_t$, the number of frames in the track, and FPS, the frames per second of the video. The second time value is derived from the estimated vehicle length ($L_v$) and the average speed of the recording device ($S_b$), which is typically a bike equipped with a speedometer. For consistency, the vehicle length is approximated based on its category, which is often set to twice its real-world size to account for the detection variability as shown in Equation (1).

$$\frac{L_t}{FPS} < \frac{L_v}{S_b} \tag{1}$$

Vehicle moving: The vehicle moving property is used to link two classes when the duration taken to cover the vehicle's observed track is calculated from the number of frames in the track and the video's frame rate is longer than the time it takes to pass the vehicle's actual physical length. The second duration is determined by the estimated length of the vehicle and the average speed of the camera during recording, as outlined in Equation (2).

$$\frac{L_t}{FPS} > \frac{L_v}{S_b} \tag{2}$$

#### *3.4.2 Logic Query description*

The illegal parking event is defined using Description Logic and is expressed as follows, which represents a vehicle that is not moving (indicated by the vehicle stationary property) and is located beneath a lane (as defined by the following relationship).

$$\exists(Vehicle\ A) \sqcap (vehicleStationary\ hasvalue{:}\ true) \sqcap below\ \exists\ Lan$$

#### *3.4.3 SPARQL for information retrieval*

This SPARQL query is crafted to answer questions, such as How, Where, What, Why, When, and Who specifically in the context of identifying illegally parked vehicles. It supports both mandatory AND and OR optional graph patterns as well as combinations using logical operators such as AND and OR, making it suitable for querying across diverse data sources. The goal of SPARQL queries is to extract meaningful semantic data, including classification, key details, metadata, complex events, and responses to specific questions. The example query below retrieves instances where an individual $i_1$ belongs to the class Vehicle and another individual $l_1$ belongs to the class Lane, with $i_1$ positioned below $l_1$ and marked as stationary (hasvehicleStationary = true).

### 3.5 Deployment of Mobile Surveillance Applications in a 5G Environment Using Multi-access Edge Computing (MEC)

Here, how 5G technology and its architecture are used to deploy surveillance applications for real-time monitoring and management within Intelligent Transportation Systems (ITS) is explained. At the edge of the network, Multi-access Edge Computing (MEC) connects the infrastructure of service providers to powerful local processing units. This setup supports applications such as surveillance and augmented/virtual reality by reducing latency and limiting the need to transmit large volumes of data to centralized processing centers. The mobile surveillance framework follows a layered service-oriented architecture consisting of three distinct levels: user, edge, and remote. At the user tier, data are gathered through devices such as unmanned aerial vehicles (UAVs) and Smart Bike Sharing Systems (SBSS), which function as user-end equipment. These devices operate dedicated applications that capture surveillance data and transmit them to the nearest edge server by using high-speed 5G connectivity. At the edge tier, incoming data are handled by a Multi-access Edge Computing (MEC) unit hosted on the server. This unit performs localized processing using built-in software tools, enabling a quick analysis close to the data source. After initial processing, the refined data are sent to the remote tier, where the cloud infrastructure manages deeper analytics and long-term storage.

## 4 Experimental Results and Discussion

The proposed EfficientDet-based smart parking system integrates a robust combination of hardware and software to enable real-time detection of illegal parking using mobile surveillance. At the hardware level, the system used a dual-camera setup with one front-facing to capture vehicle number plates and one side-facing to monitor roadside activity mounted on a mobile unit, such as a smart bike or UAV. These units are equipped with GPS modules, speed sensors, and onboard processing capabilities, ideally powered by edge devices, such as NVIDIA Jetson Xavier NX or Orin Nano, which offer sufficient GPU cores and memory for real-time inference. The captured data are transmitted through a 5G network to a Multi-access Edge Computing (MEC) node, where it is processed locally to reduce latency. On the software side, EfficientDet serves as the central object-detection model, offering high accuracy with minimal computational overhead. Lane detection is performed using OpenCV-based techniques such as Gaussian blur, Canny edge detection, and Hough transform, whereas vehicle registration numbers are extracted using Tesseract OCR v4. The Smart Park ontology organizes sensor and visual data into an RDF format, enabling semantic reasoning through SWRL rules and SPARQL queries. This fusion of advanced hardware and intelligent software ensures scalable privacy-preserving surveillance without the need to store full video footage, making it ideal for dynamic urban environments.

### 4.1 Evaluation Metrics

Evaluation metrics are used to validate the performance of the proposed smart parking detection system with EfficientDet, including accuracy, precision, and recall, which collectively reflect the system reliability in identifying illegal parking events. The metrics are derived from object detection outputs and semantic reasoning results, where high values across all indicators confirmed the effectiveness of the EfficientDet model and ontology-based inference.

- Accuracy: Accuracy is the overall accuracy of the system in identifying both illegally parked and properly parked vehicles shown in Equations (3)-(5).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

- Precision: Precision measures how many of the vehicles identified as illegally parked actually violated parking rules.

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

- Recall: Recall evaluates the number of illegally parked vehicles successfully detected by the system.

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

### 4.2 Performance Evaluation

Table 1 presents the performance evaluation of the baseline smart parking methods, which is a reference for evaluating technological advancements. It captures key metrics across various systems to highlight their strengths and limitations in real-world applications.

**Table 1.** Quantitative analysis of baseline models.

| Models | Accuracy (%) | Precision (%) | Recall (%) |
|---|---|---|---|
| IoT-Based Sensor Networks | 95.78 | 94.28 | 95.13 |
| Automated Parking Systems (APS) | 91.27 | 90.08 | 90.75 |
| Cloud-Based Parking Platforms | 94.71 | 94.64 | 93.98 |
| EfficientDet-Based Smart Parking System (proposed) | 98.4 | 97.67 | 98.04 |

### 4.3 Statistical Test

A paired t-test is the most suitable method for statistically validating the performance improvements introduced by the proposed EfficientDet-based smart parking system. This test compares the system's accuracy, precision, and recall before and after integrating semantic components, such as the SmartPark ontology, SWRL rules, and SPARQL queries. By analyzing paired results from identical test sequences under different configurations, the t-test determined whether the observed improvements increased from 93.04% to 98.40% in accuracy, which is statistically significant rather than due to random variation. This approach strengthens the reliability of the evaluation and supports system effectiveness in real-world deployment.

### 4.4 Ablation Study

Table 2 presents the performance of the proposed system under incremental architectural enhancements. Each configuration is measured to demonstrate how semantic reasoning and ontology integration contributed to the improved detection accuracy.

**Table 2.** Performance evaluation of each component of the proposed EfficientDet-based smart parking system.

| Components | Accuracy(%) | Precision(%) | Recall(%) |
|---|---|---|---|
| Baseline EfficientDet | 93.04 | 92.87 | 92.74 |
| EfficientDet + Ontology | 94.68 | 93.87 | 93.07 |
| EfficientDet + Ontology+ SWRL | 89.14 | 88.74 | 89.07 |
| EfficientDet + Ontology + SPARQL | 93.57 | 92.57 | 93.04 |
| EfficientDet + Ontology + SWRL + SPARQL (proposed) | 98.4 | 97.67 | 98.04 |

### 4.5 Comparison Study

Figure 2 presents a comparative analysis of the proposed EfficientDet-based smart parking system and other state-of-the-art methods. The comparison highlights the differences in detection accuracy, precision, and recall across various architectures, including LLM-enhanced ontologies, YOLOv5s with attention modules, and 5G-enabled MEC frameworks. This evaluation underscores the superior performance of the proposed system in terms of semantic reasoning, real-time responsiveness, and overall reliability of detection.

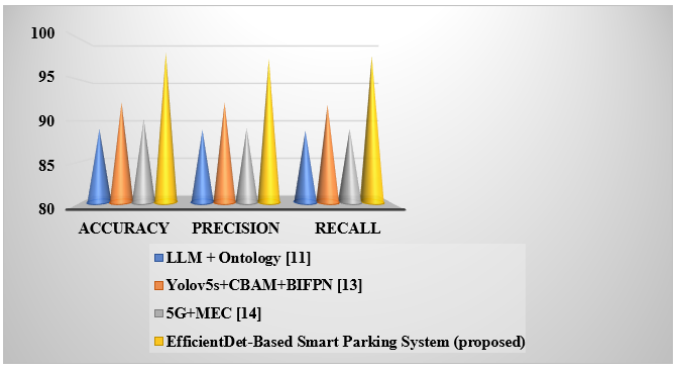


**Fig. 2.** Comparison of proposed EfficientDet-based smart parking system with existing methods.

### 4.6 Discussion

The proposed EfficientDet-Based Smart Parking System demonstrates significant advancement in real-time illegal parking detection by integrating EfficientDet with semantic reasoning components. It consistently achieves higher accuracy, precision, and recall than existing smart parking solutions, as shown in the comparative evaluation. The use of SmartPark ontology enables structured representation of surveillance data, whereas SWRL rules and SPARQL queries enhance the system's ability to infer complex parking violations without depending on full video storage. Mobile surveillance units equipped with dual cameras and edge-processing hardware ensure scalability and responsiveness in dynamic urban

environments. The system maintains privacy by transmitting only annotated metadata rather than raw footage. Furthermore, the deployment of 5G and Multi-access Edge Computing (MEC) infrastructure reduces latency and supports real-time decision-making. The ablation study confirms that each architectural enhancement ontology, SWRL, and SPARQL contribute incrementally to the performance gains. Compared with models such as YOLOv5s-C&B and LLM-enhanced ontologies, the proposed method exhibits superior semantic depth and detection reliability. These results validate the suitability of the proposed system for large-scale adaptive smart parking enforcement.

## 5 Conclusion

The proposed EfficientDet-based smart parking system achieved superior performance in detecting illegal parking events using mobile surveillance and semantic reasoning. The results validate the effectiveness of integrating EfficientDet with the SmartPark ontology, SWRL rules, and SPARQL queries for real-time, privacy-preserving detection. The proposed EfficientDet-based smart parking system provides an accuracy of 98.4%, precision of 97.67%, and recall of 98.04%, performing better than baseline models, such as IoT-based sensor networks and cloud-based platforms. For future enhancement, the system can incorporate adaptive ontologies that evolve with changing traffic regulations and urban layout. Integration with Large Language Models (LLMs) can further improve rule generation and semantic interpretations. Additionally, expanding the system to support multimodal inputs such as LiDAR, thermal imaging, or audio signals may enhance the detection accuracy under low-visibility or occluded conditions. These improvements will extend the robustness and applicability of the system to broader smart city deployments.

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