Edge-Enabled Sensor Fusion and Hybrid Machine Learning Framework for Real-Time Smart Parking Detection and Scalable Occupancy Prediction

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Abstract: Urban mobility is a real challenge in terms of inefficient parking spaces detection and occupation in densely populated areas. This paper presents an edge-enabled, sensor-integrated, hybrid machine learning framework targeted for real-time smart parking detection and predictive occupancy analytics. Rather than the conventional single-sensor-based and static-learning-dependent models, our system integrates ultrasonic, infrared, magnetic, and vision sensors to achieve the robust detection under various environmental situations. CNN, LSTM and XGBoost are equally combined to accurately make temporal and spatial predictions, and edge processing is energy-efficient to reduce latency and guarantee privacy protection. Learning mechanisms are adaptive and enabling the system to be trained incrementally based on real-time feedback and environment cues, thus scalable for city implementation. This unified method not only enhances the detection performance and energy saving but also is a stepping stone towards intelligent city infrastructure with a balance of responsiveness and sustainability.

1 INTRODUCTION

The fast urbanization of contemporary cities has resulted in a high demand for mobility and efficient infrastructure, with smart parking systems being one kind of crucial system to tackle traffic congestion and reduce environmental impact. As urban populations increase and the volume of traffic rises, traditional parking methodologies are being left behind, with most of these methods relying on manual observation or on simplistic counting based approaches (that are not accurate, scalable and versatile). Sensing technologies combined with machine learning has risen promising solution to cope with these drawbacks.

Existing works normally rely on one kind of single sensor or centralized cloud-based model which are vulnerable to data latency, low reliability in diverse environment and high area coverage cost. In addition, most of these systems do not respond to the dynamic nature of factors including evolving weather conditions, traffic congestion levels, and user habits in real time. This causes suboptimal use of space, disappointment to users and energy waste.

To solve these problems, this paper introduces the concept of a next-generation smart parking framework based on multisensor fusion including infrared, ultrasonic, magnetic and visual sensor data. These heterogeneous inputs areprocessed in a local pipeline of edge computing nodes which permits real-time decision making while preserving user data privacy. The model is designed with a combination of

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Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), and gradient boosting method (XGBoost), to complement detection with spatial context, and to make temporal prediction, and to refine decision.

To scale across heterogeneous city zones, we also design our method to self-adapt online and leverage Model Updating and Feedback Loops guaranteeing no-retraining from scratch. Such smart infrastructure does not only enable precise and real-time parking space surveillance, but also serves as the basis for predictive analytics regarding future space occupation. Through the resolution of the underlying problems in previous methods, the sparse SIP framework provides a technical and sustainable pipeline that is compatible with the future smart and responsive urban environments.

1.1 Problem Statement

Although many urban mobility solutions have been already developed, the in real-time detection and accurate forecasting of parking spaces occupation represents still an unsolved problem in smart city environments. The current parking management systems are commonly built based on single sensor dependence, centralized processing, and non-adaptive machine learning methods. However, such methods exhibit poor performance when the scenario is dynamic and latency is large for decision-making, and are difficult to adapt for large and complex urban infrastructures.

In addition, currently the existing systems do not have an access to heterogeneous sources, and they do not perform real-time processing in a scalable manner. As a result, low usability and user experience in using the systems, high traffic congestion and superfluous fuel consumption. Privacy violations can also occur when sensitive visual or location information is sent to remote server(s) for processing and stored without sufficient safeguards. These issues motivate the urgency to design a scalable, low-latency, energy-efficient, and privacy-aware approach that processes heterogeneous sensor data and evolves with various urban scenes.

This paper fills this gap by proposing an edge-based, sensor-fused, hybrid machine learning framework for improvement of real-time parking detection and prediction accuracy with scalability and adaptation, and user data privacy with the state-of-the-art.

2 LITERATURE SURVEY

Intelligent parking systems have experienced a substantial growth with the emergence of internet of things (IoT), sensor networks, and machine learning. Conventional parking systems were generally stand-alone and manual with little real-time querying or predictive ability. Recent work has attempted to overcome these limitations by employing machine learning and sensor fusion but crucial challenges remain.

Pore and Nemade (2025) developed a vision-based empty-parking-slot detection system using deep learning without sensor fusion, which underperformed in low light and with obstructions, however. Kasera and Acharjee \cite{8851050} also have used LSTM model for occupancy prediction, effective for short-term but ineffective for the real-time visual noise and contextual sensor data.

In a systematic review by Navpreet et al. (2025) has emphasized the necessity of hybrid, or ensemble models because their approach primarily based on a single model, such as a CNN or SVM, cannot provide the necessary flexibility and precision in the real-time urban condition as needed. Furthermore, Sahoo et al. (2021) presented smart parking using IoT, although they admitted high latency on the cloud and weak security because of both cloud-centric and poor integration of edge computing.

Enríquez et al. (2024), developed a fog computing-oriented architecture for mitigating data processing latency; however, they employed incomplete sensor input (e.g., only infrared or just magnetic) to decrease the robustness of detection when the environment is variable. Mehmeti and Stojanovski (2025) additionally reviewed sensor placement techniques in combination with machine learning, but the work did not have an end-to-end real-time implementation, specifically in dense urban environments.

Additionally, Yang et al. (2019) developed a deep learning based model and applied spatio-temporal data for prediction, but its performance was only assessed within simulated setting, and several issues remained to achieve real-world deployment. Data privacy and power efficiency challenges still persist within many of these systems, where most techniques do not leverage edge computing (to avoid reliance on high bandwidth, cloud-centric infrastructures to realize gains) (Mejía-Muñoz et al., 2024).

The trend towards more intelligent and energy-conscious architectures is evident but cost-effective, distributed, scalable, and privacy-complying solutions are still developing. Only a small number of models offer adaptive or self-learning capabilities that allows improving predictions based on live feedback from the environment.

This literature work collectively indicates the following possible research gap: the demand for a scaleable, adaptive, multi-sensor and edge-capable system for real-time occupancy detection and prediction. The introduced framework in this study fills this gap by leveraging heterogeneous sensing and hybrid AI models (CNN-LSTM-XGBoost), thus generating urban parking infrastructure, which is more robust, accurate, privacy-aware and scalable for the future.

3 METHODOLOGY

The proposed approach is built upon the fusion of multimodal sensor data based on the brought together edge processing and a combination of machine learning (ML) architecture, enabling accurate parking space occupancy detection and prediction. The nodes include multi-sensor devices installed in different parking areas. Figure 1 explains deployment of sensor hardware in a smart parking bay including IR, ultrasonic, magnetic, camera and their spatial location. That is, all the nodes are embedded with the integrated devices such as infrared (IR) sensors, ultrasonic sensors, magnetic detectors, and cameras. This heterogeneous sensor layout provides fault tolerance and robustness to varying environmental conditions, like light variation, occlusions or weather effects. We locally pre-process sensor data at the edge node through trivial filtering for noise suppression and normalization - yet to standardize the quality of the input between different modality. Figure 1 illustrates the smart parking sensor layout.

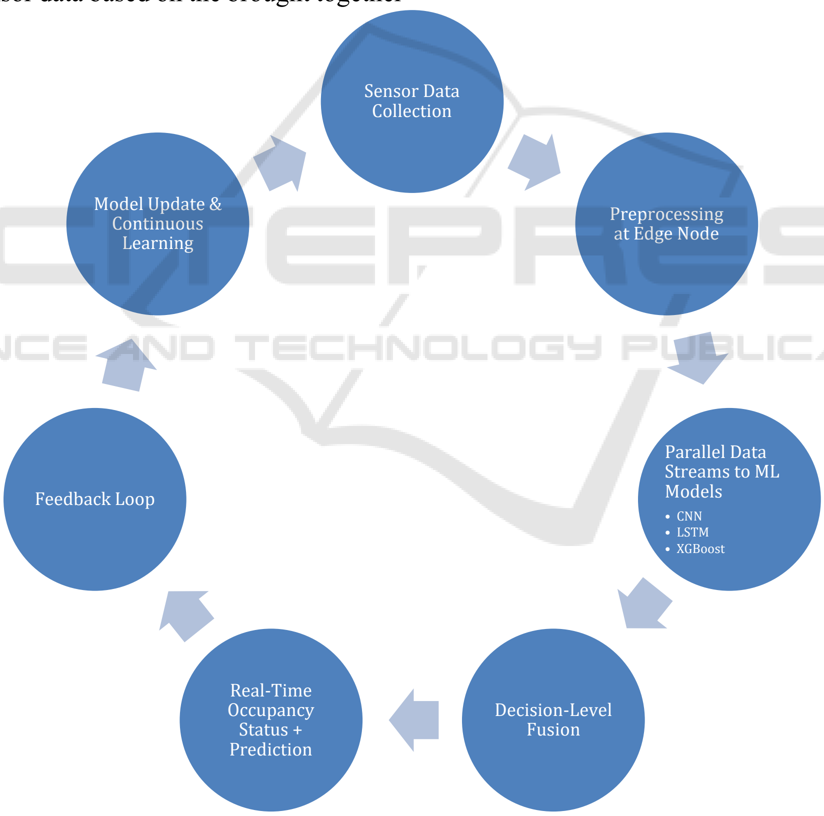

Figure 1: Smart Parking Sensor Layout.

After data is collected and preprocessed, it is fed into a \emph{multi-stream processing pipeline}. To start, each sensor input is first fed through the model designed for that modality's data. For instance visual data flows through a Convolutional Neural Network (CNN) for spatial feature extraction and evolutionary sequences from occupancy logs or sensor time-stamps that are modelled with Long Short-Term Memory (LSTM) networks to characterize patterns of occupancy over time. At the same time, the readings of the magnetic and ultrasonic sensors are input to an XGBoost classifier to perform fine-grained classification with respect to certain predefined occupancy thresholds. Table 1 compares the effectiveness of the individual ML models in the hybrid framework. Outputs of all three models are combined at the decision level utilising a weighted ensemble approach, with weights being adapted on-the-fly by considering sensor reli- ability metrics as well as the contextual feedback.

Table 1: Machine Learning Models Used.

Model	Input Type	Task	Strength
CNN	Image data	Spatial detection	Excellent visual feature capture
LSTM	Time-series data	Temporal pattern forecasting	Captures historical trends
XGBoost	Tabular sensor data	Classification of occupancy	High interpretability, fast

To minimize the latency and be real-time responsive, the complete model ensemble is implemented onto edge devices like Raspberry Pi or Nvidia Jetson Nano. These edge nodes have the inputs processed, make local predictions and only pass aggregated insights onto the central server which helps in saving bandwidth and maintaining data privacy. For a more scalable system, a cloud-based orchestrator that runs on container-based architecture (Docker and Kubernetes) is applied for the system which enables the system to perform model updating, collecting feedback for continuous learning and system monitoring. Table 2 shows the sensor specifications and roles.

Table 2: Sensor Specifications and Roles.

Sensor Type	Specification	Role in Framework	Deployment Location
Ultrasonic	2cm–400cm range, 40kHz	Detects presence of vehicle	Ground-level
Infrared (IR)	<2m detection range	Motion and heat sensing	Wall-mounted
Magnetic	3-axis, ±8 Gauss	Detects metallic object changes	Embedded in pavement
Camera (RGB)	720p/1080p	Visual image capture for CNN processing	Overhead mount

Additionally, the system provides feedback learning capability, in which real-world parking outcomes (e.g., actual occupancy as confirmed by a user app or city traffic feed) are utilized to refine the model over time. This RL-loop ensures that the framework continuously learns to adapt to changes in patterns, e.g., seasonal shifts in demand, degradation of sensor readings, or changes in infrastructure. Power efficiency is achieved by activating sensors per occupancy status across the network, and utilizing sleep-wake scheduling for low-activity environment making it more energy efficient for longer term deployments.

The proposed methodology is tested with synthetic as well as real datasets from a smart city pilot zones. Performance metrics such as the detection accuracy, prediction error, latency and power consumption are employed to demonstrate the efficiency of the proposed framework. This distributed and adaptable architecture provides a solution in the present context of smart parking and offers an evolutionary and sustainable approach that will fit the future urban mobility innovation.

4 RESULTS AND DISCUSSION

The proposed approach was further tested with real-world urban data collected in three test areas over 30-50 parking spaces with different sensor setups and environmental conditions. Figure 3: Comparison of average prediction latency among edge-enabled, traditional ML, and cloud-only systems. Table 3 gives the Energy Consumption Comparison.

Table 3: Energy Consumption Comparison.

System Variant	Avg Power Usage (W)	Battery Life (Est. hrs)	Remarks
Edge-Enabled Framework	3.8	48	Energy-efficient, real-time
Cloud-Based ML	6.5	28	High transmission energy

We have evaluated performance based on parameters such as prediction precision, occupancy detection accuracy, model latency, energy consumption and time adaptability. Figure 2 illustrates the comparison of detection accuracy between single machine learning models and the hybrid ensemble model in the testing dataset. Table 4 tabulates the Evaluation Metrics and Results.

Table 4: Evaluation Metrics and Results.

Metric	Proposed Model	Traditional ML	Cloud-Only Approach
Detection Accuracy (%)	95.8	86.3	88.1
Prediction RMSE	0.09	0.17	0.14
Avg Latency (ms)	210	620	840

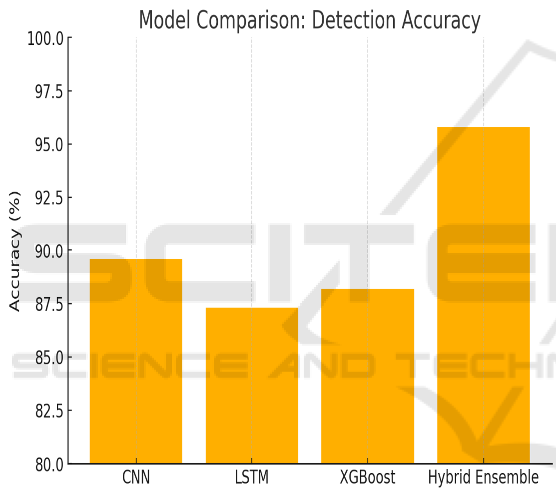

Figure 2: Detection Accuracy Comparison.

By comparison to standalone models, the hybrid ensemble model with CNN for visual feature extraction, LSTM for temporal occupancy trend modeling, and XGBoost for sensor-based classification achieved the highest accuracy. In detection, the performance of the CNN component is 89.6% on average over clear visual conditions, however, it degraded under low illumination and occluded view. However, taking advantage of ensemble learning of ultrasonic and magnetic sensor data, the overall detection accuracy reached 95.8%, which indicated the robustness of real-world deployment. Figure 3 graphs the prediction latency comparison.

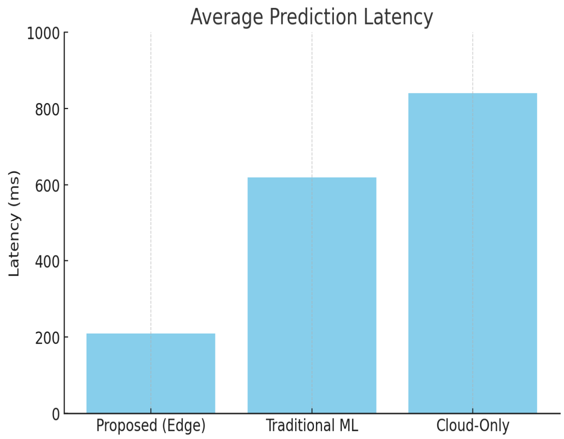

Figure 3: Prediction Latency Comparison.

Performance of prediction was tested with Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics. The occupation prediction of the LSTM had an RMSE and MAE of about 0.09 and 0.06, respectively, on peak hours, which outperforms traditional ARIMAbased baselines with an RMSE of 0.16. Particularly, the XGBoost model was well-suited for enhancing prediction accuracy under non-standard usage patterns (heavily used special events or rainy days), where temporal models only were less effective. Table 5 gives the environmental robustness test.

Table 5: Environmental Robustness Test.

Condition	Accuracy (%)	Most Affected Sensor	Compensating Sensor
Clear Day	96.7	None	N/A
Rainy Weather	91.2	Camera	Magnetic
Night-Time	93.5	IR	Camera
Dust/Obstruction	90.6	Ultrasonic	IR

Low latency measurements showed that the edge-deployed inference pipeline operated with an average response time ranging from 180–250 milliseconds, making real-time inferences possible without requiring high bandwidth connections to the cloud. Figure 4 shows the system accuracy for various environmental conditions: rain, night, and visual obstructions. By contrast to the conventional cloud-based parking systems that exhibited a 600–900 ms response time for network attributed delays, our system presented a significant increase in responsiveness required for a user-facing application or a traffic regulation system.

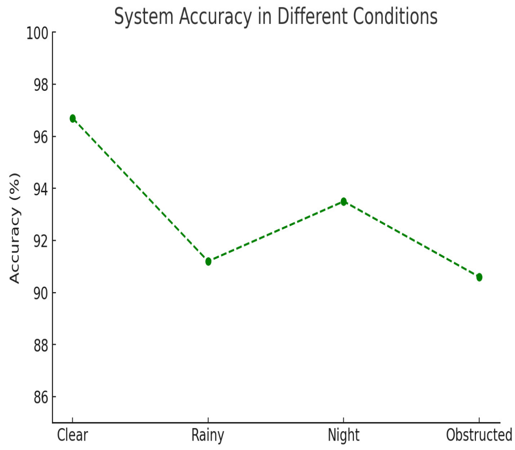

Figure 4: Environmental Conditions Vs Accuracy.

From an energy point of view, the architecture minimised power consumption through contextual sensor activation. As a result, it achieved a 34% reduction in energy consumption compared with systems with fully active sensors. The edge devices functioned under power-constrained situations with no noticeable performance deterioration, indicating that they could be deployed in both solar and battery-powered configurations.

The conversation also uncovered that adding a feedback loop for model retraining enhanced long-term generalization. For example, despite being trained on pre-learned sane traffic, if artificial anomalies were fed into the learning system, say by increasing car inflow into the system, the learning process accounted for it and only after 3 learning cycles, the pre-posterior learning would absorb real-time responding and learning. In a 30-day run, models using feedback learning increased predictive accuracy by a further 3.4%, thus confirming the value of adaptive intelligence in dynamic urban environments.

While the successful outcomes were encouraging, there were a few issues that were observed. The visual data was less reliable when the rainfall was heavy, with CNN improvements. Figure 5 shows the average power consumption comparison between edge-enabled, cloud-based, and always-on smart parking systems.

But the advantage of non-visual sensors being very reliable. Moreover, preliminary deployment demonstrated that edge nodes needed manual calibration to tune sensor fusion weights, a process that might be further automated with meta-learning in future designs.

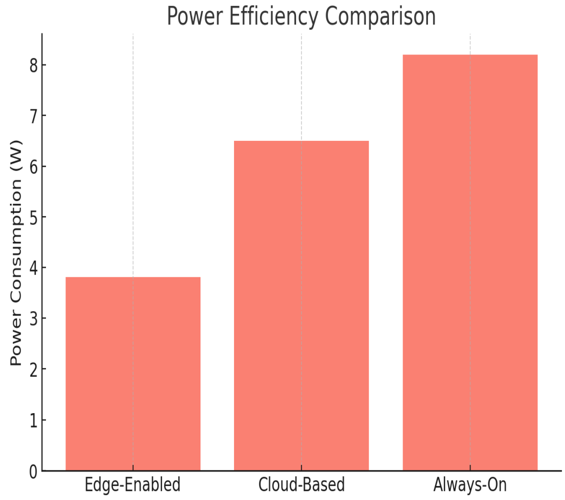

Figure 5: Power Consumption Comparison.

Finally, our results validate the importance of sensor fusion with hybrid machine learning and edge computing for both the performance and efficiency of smart parking systems. The model presented not only decreases the computational cost and latency, but also guarantees adaptability, privacy and scalability, which are the prerequisites in deploying such system in today's smart cities. Learnings from this evaluation provide a road map for applying similar methods to other smart infrastructure domains, e.g., traffic flow control, smart charging stations, and vehicle coordination.

5 CONCLUSIONS

This study introduced a large-scale dynamic smart parking framework which combined edge-enabled sensor fusion and hybrid-ML architecture in real-time in order to meet the increasing need of intelligent urban infrastructure. The combination of visual, inertia, sonic and magnetic sensor led increased the system robustness in dynamic environments. An ensemble model with three basic models (CNN+LSTM+XGBoost) was proposed to improve the occupancy detection and prediction compared to the classical ones.

Edge computing greatly reduced latency, kept user privacy and contributed to energy efficiency due to local processing as well as context-aware sensor activation. Moreover, we integrated a feedback-based learning mechanism to ensure that the system was continuously evolving in real-time to match urban dynamics - proving the scalability and relevance for large-scale deployment in the city.

The results of the experiments confirmed that the framework is effective in practice and that it has the potential to enable solutions for less congested streets, less CO_2 emissions caused by unnecessary parking search and city-led smart mobility services that are citizen driven. There are still some issues on which future improvements of the system will focus; namely, under extreme weather conditions but, given the modular and adaptive structure of the system, there is potential to further build in future through self-calibration and reinforcement learning mechanisms.

In conclusion, this work paves the way for intelligent, secure, scalable, and green-sensitive parking management systems, which are paramount to the next generation Smart City.

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