Original Article

AI-based license plate recognition for tourist dynamics analysis and sustainable tourism management in Shirakawa-go

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Abstract

This study proposes an AI-based license plate recognition system deployed at parking areas in Shirakawa-go, a UNESCO World Heritage site, to analyse and visualize tourist dynamics. The system automatically detects and recognizes vehicle license plates from camera footage, enabling large-scale and continuous monitoring of tourist traffic patterns. The extracted data provide insights into visitor origins, stay durations, visit frequencies, and rental car usage, offering valuable indicators for regional tourism management. Compared with conventional manual counting and questionnaire surveys, the proposed approach enables efficient, automated, and continuous data collection suitable for small-scale destinations with limited resources. The empirical operation in Shirakawa-go demonstrated that the system can identify temporal peaks in parking demand and support cloud-based data aggregation for real-time analysis. These findings highlight the system's potential for overtourism mitigation, parking congestion alleviation, and data-driven resource optimization, thereby contributing to sustainable and responsible tourism management in culturally significant rural areas.

Keywords

license plate recognition, tourist dynamics analysis, overtourism mitigation, deep learning, digital transformation in tourism

1. Introduction

In recent years, the issue of overtourism has increasingly drawn global attention in the field of tourism management. It refers to situations where the number of visitors exceeds the local carrying capacity, resulting in negative consequences such as traffic congestion, environmental degradation, cultural erosion, and a decline in residents' quality of life. This phenomenon poses particularly serious challenges for small-scale destinations with limited financial and human resources. In Japan, overtourism has long been recognized as a serious issue, particularly in popular cultural and historical destinations. Although inbound tourism temporarily declined during the COVID-19 pandemic, visitor numbers quickly returned to pre-pandemic levels once border restrictions were lifted and have since shown a further upward trend. The number of international visitors reached 3.91 million in April 2025, the highest monthly record ever [Japan National Tourism Organization, 2025]. This rapid recovery has placed increasing pressure on culturally and historically significant destinations such as Kyoto, Kamakura, and Shirakawa-go, where a sudden influx of tourists has strained local infrastructure, disrupted community life, and threatened the sustainability of heritage landscapes.

Shirakawa-go, designated as a UNESCO World Heritage site, is world-renowned for its distinctive Gassho-zukuri thatched roof houses and scenic rural landscape. However, the continuous growth of both domestic and international visitors has increased pressure on the area's limited transportation and parking capacity, as well as on its fragile environment and local community. In 2024, the total number of tourists visiting Shirakawa-go reached approximately 2.08 million, whereas as of 2025, the local population stands at only 1,453 residents (around 600 households) with an aging rate of 33.54% [Shirakawa village, 2025]. These challenges highlight the urgent need for scientific, data-driven, and efficient methods to monitor, analyse, and manage tourist flows. Traditional approaches, such as on-site manual counting and questionnaires, require considerable manpower and are difficult to sustain over long periods. Consequently, the lack of reliable, real-time data often hampers evidence-based decision-making in tourism policy and management.

To address these challenges, this study proposes an AI-based License Plate Recognition (LPR) system designed to monitor and analyse tourist dynamics in Shirakawa-go (Figure 1). The proposed framework consists of three main stages: data collection, analysis, and utilization. In the data collection stage, a fixed camera installed at the entrance of the parking area automatically detects and recognizes vehicle license plates. From the captured video, the system extracts structured data such as vehicle origin, rental car identification, bus identification, number of vehicles, and length of stay. This process enables automated and continuous acquisition of large-scale tourism mobility data. In the analysis stage, the collected data are processed to generate quantitative indicators of tourist behaviour, including tourist route analysis, rental car classification, hourly vehicle counting, tourist flow estimation, and peak-hour detection. These analyses provide detailed insights into temporal and spatial patterns of visitor dynamics. In the utilization stage, the results are applied to practical tourism management tasks such as congestion monitoring, parking lot status monitoring, and

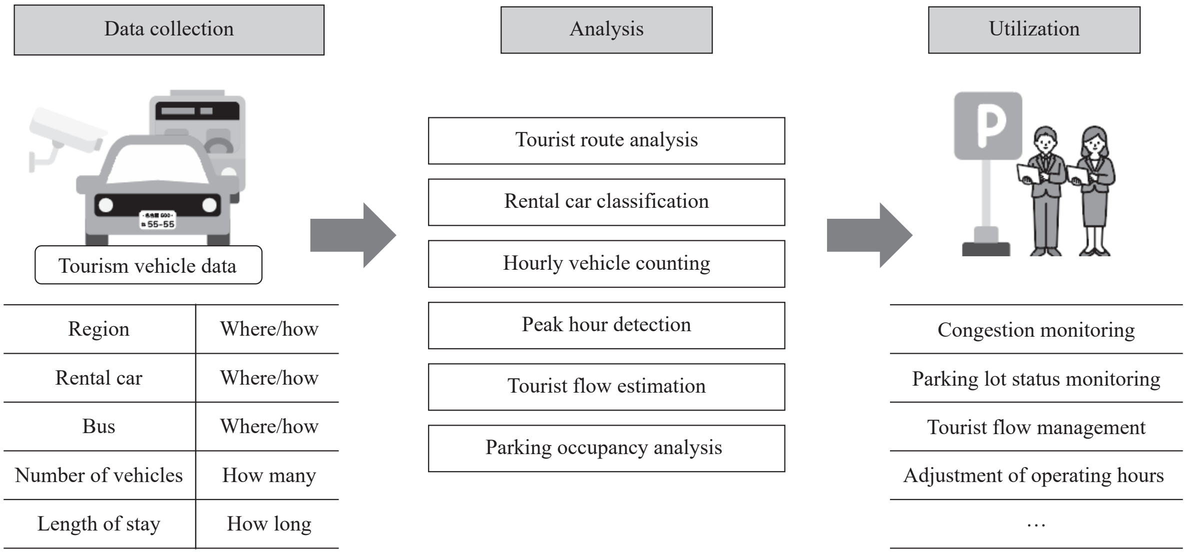

Figure 1: Overview of the proposed system

tourist flow optimization. The derived insights also support operational decisions, including staff allocation and the adjustment of parking or facility operating hours, thereby contributing to sustainable and data-driven overtourism mitigation.

The main contributions of this study are summarized as follows:

- This paper presents the design and implementation of an AI-based LPR system specifically tailored to rural heritage destinations such as Shirakawa-go, addressing the unique challenges of limited infrastructure and human resources in small-scale tourism areas.
- It demonstrates how the proposed system can quantitatively visualize and analyse tourist dynamics, including vehicle inflow and outflow patterns, stay durations, and visitor origins, to support data-driven management and decision-making at local destinations.
- It further discusses the potential applications of AI-driven data collection and analysis in promoting sustainable tourism management, highlighting the role of intelligent monitoring systems in mitigating overtourism and optimizing the use of regional resources.

2. Related work

Research on the use of AI and object detection technologies in tourism and mobility management has expanded rapidly over the past decade. With the advancement of deep learning architectures and the increasing availability of real-time sensing data, AI systems are now capable of performing complex recognition, prediction, and optimization tasks that were previously labor-intensive. In the context of tourism management, these technologies have been applied to diverse objectives such as visitor-flow measurement and analysis, resource optimization, and destination sustainability assessment.

The literature relevant to this study can be broadly classified into three domains. First, advances in LPR and object detection have laid the technical foundation for mobility analytics and intelligent transportation systems (ITS). Second, the integration of AI and deep learning into tourism and cultural heritage management has enabled automated data collection, personalized visitor experiences, and efficient regional promotion. Finally, a growing body of work addresses the management of overtourism and the application of smart technologies to enhance sustainability in resource-limited destinations. The following subsections summarize these research streams in detail and position the present study within this broader research landscape.

2.1 Advances in object detection and LPR

Recent progress in deep learning-based object detection has dramatically improved the accuracy and efficiency of visual recognition systems. Modern architectures such as YOLO, EfficientDet, and Transformer-based detectors have achieved a balance between real-time processing and recognition precision, enabling practical applications on edge devices and in complex outdoor environments [Zou et al., 2020]. Building upon these developments, LPR technology has also evolved significantly. Traditionally utilized for traffic surveillance and law enforcement, LPR has now become an integral component in smart city infrastructures and ITS [Gao et al., 2024]. In recent IoT-based developments, a smart parking management framework integrating LPR and sensor networks has demonstrated strong recognition performance and reliable automation of parking operations, confirming its applicability for large-scale urban environments [Rajesh et al., 2025]. Their system achieved high recognition accuracy under various illumination and weather conditions, demonstrating the feasibility of large-scale deployment in urban contexts. Furthermore, Sonnara et al. developed an efficient real-time license plate recognition system optimized for edge-device deployment, focusing on lightweight model architectures and on-device inference acceleration. Their experiments on embedded hardware platforms achieved real-time performance without reliance on cloud processing, proving that high-accuracy LPR can be realized even under strict computational and latency constraints. This study underscores the growing trend toward distributed, energy-efficient computer vision systems and highlights the feasibility of deploying LPR technology in resource-constrained or rural environments [Sonnara et al., 2025].

In addition, a comprehensive review examined the technological evolution of automatic number plate recognition (ANPR) within the broader context of smart-city development. The study systematically compared algorithmic advances from traditional image processing to deep convolutional and Transformer-based frameworks and evaluated real-world deployment cases across multiple countries. It emphasized that recent progress in deep learning and IoT integration has expanded ANPR applications beyond traffic enforcement to include urban mobility management, parking optimization, and environmental monitoring. The authors also identified persistent challenges such as privacy protection, dataset bias, and model robustness under adverse weather conditions, underscoring the need for adaptive and ethical AI solutions in future smart-city systems [Tang et al., 2022].

These studies collectively demonstrate that AI-driven visual sensing systems can provide scalable and automated data collection frameworks for managing mobility and environmental challenges.

2.2 AI applications in tourism and cultural heritage

Beyond transportation and urban analytics, our research group has actively explored the potential of AI and computer vision in regional tourism management, particularly in data collection, visitor engagement, and cultural heritage preservation. We developed a deep learning-based image processing system for local governments, capable of automatically detecting faces, classifying seasonal features, and generating captions for tourism photographs. The system enables municipalities to anonymize personal information while promoting scenic assets, effectively reducing administrative burdens and enhancing the efficiency of digital tourism promotion [Tu et al., 2022]. In addition, we designed a low-cost and multilingual audio guide system tailored for small-scale historical buildings. The system utilizes generative AI to streamline the creation and updating of audio content and is designed for ease of use by local volunteers and facility managers. Field experiments conducted in Nagoya's Cultural Path Area confirmed that the approach improves visitor satisfaction and accessibility while reducing operational costs, thereby contributing to sustainable and community-driven tourism development [Bian et al., 2025].

Complementing these more recent developments, earlier work addressed overtourism in historic European city centers by combining visitor-flow monitoring with spatial analytics [Zubiaga et al., 2019]. Their study introduced a framework for real-time pedestrian tracking to assist municipalities in balancing heritage preservation and visitor pressure, paving the way for data-informed destination governance. Collectively, these studies emphasize that AI technologies, ranging from visual analytics to generative models, are becoming indispensable tools for achieving sustainable, inclusive, and community-driven tourism development.

2.3 Research gap and motivation

Although LPR and AI-based tourism applications have achieved considerable progress, empirical research on the deployment and evaluation of LPR systems in small-scale tourism destinations remains scarce. Most existing studies focus on urban contexts or large-scale infrastructures, leaving a gap in understanding how such systems perform under rural, culturally sensitive, and resource-constrained conditions.

Most existing studies focus on urban contexts or large-scale infrastructures, where traffic monitoring systems, sensor networks, and extensive datasets are readily available. In contrast, rural areas and small-scale tourist destinations have received limited attention due to several practical constraints. These include the lack of existing surveillance infrastructure, difficulties in securing equipment installation sites, limited budgets for continuous monitoring, and the perception that detailed mobility data were not urgently required in local tourism management. These structural and operational barriers have historically made empirical studies in rural contexts technically challenging and costly. Against this backdrop, the present study implements an AI-based LPR system in Shirakawa-go, a UNESCO World Heritage site, to evaluate its capability in monitoring tourist dynamics, mitigating overtourism, and supporting sustainable tourism management. By demonstrating how mobility-focused data can inform local decision-making and smart destination strategies, this work contributes practical insights to both computer vision research and tourism informatics.

3. Proposed method

This study proposes an AI-based LPR system designed to meet the growing demand for automation and scalability in the management of small-scale cultural tourism destinations. The system is optimized for rural heritage sites such as Shirakawa-go, where budgets, personnel, and technical infrastructure are limited. Its primary objective is to provide real-time data on tourist traffic patterns, alleviate parking congestion, and support data-driven and sustainable tourism governance. The proposed framework consists of three major modules and a four-step operational workflow, as described below.

3.1 System architecture overview

The overall system is composed of three functional modules.

- Vehicle and LPR Module

This module performs real-time detection of both vehicles and license plates from continuous video streams or captured images. It employs YOLOv8, a lightweight yet highly accurate deep-learning model optimized for edge-device deployment [Jocher et al., 2023]. The model can maintain stable inference under varying illumination, weather, and camera-angle conditions, making it suitable for continuous outdoor operation. Each detected object is assigned a bounding box and confidence score, which are passed to the subsequent recognition module.

- End-to-End License Plate Detection and Attribute Inference Module
  Unlike conventional two-stage LPR pipelines that rely on a separate OCR engine, the proposed system adopts an end-to-end recognition strategy using YOLOv8. The model is trained on a large-scale, manually annotated dataset of Japanese license plate images, which includes multiple lighting conditions, angles, and vehicle types (private and rental) [Roboflow Universe, 2025]. Data augmentation techniques, such as random scaling and horizontal flipping, were applied to enhance model generalization. From each detected plate, individual characters are localized and classified, and then reassembled according to positional and structural rules to form the complete plate number. Based on the recognized results and predefined plate formats, the system automatically infers key vehicle attributes: (a) registration region (prefecture or city), (b) vehicle type (private or rental), (c) license plate number, and (d) detection timestamp (Figure 2).
- Data Structuring and Cloud Integration Module
  This module structures the recognition outputs into standardized CSV files and synchronizes them to a cloud platform (e.g., AWS S3 or Google Drive). It enables long-term data access and visualization for municipal and research purposes.

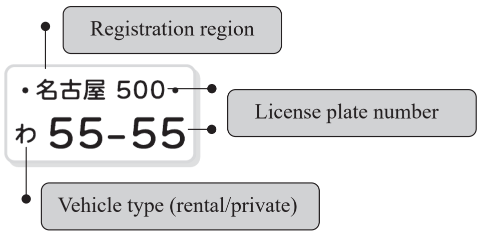

Figure 2: Example of Japanese license plate

3.2 *Operational workflow*

The proposed system follows a four-step processing workflow that automates data acquisition, detection, optimal-frame selection, recognition, and structured data generation. The entire pipeline operates continuously on a local edge device to ensure efficient and stable performance in rural environments.

- Image Capture
  A fixed camera is installed at the entrance of the parking area to continuously record vehicle movements at a resolution of 1920 × 1080 pixels and a frame rate of 25/30 FPS. The cameras are mounted at a height of approximately 3-4 meters and angled to minimize occlusion while maintaining visibility of approaching vehicles under varying weather and lighting conditions. Captured footage is transmitted to an edge-computing device for real-time processing.
- Frame Sampling and Vehicle Detection
  The system periodically samples frames from the incoming video stream (e.g., every 0.5-1.0 seconds) and applies the YOLOv8-based model to detect vehicles. When a vehicle is detected, the corresponding frame is automatically extracted and saved for further analysis.
- Optimal Frame Selection and License Plate Recognition
  For each vehicle, multiple frames may contain the license plate. To ensure recognition stability, the system automatically selects the frame in which the detected plate occupies the largest visible area. The selected frame is then passed to the end-to-end recognition module, which directly outputs the full license-plate string and associated attributes.
- Data Export and Cloud Synchronization
  The structured recognition results are automatically saved and synchronized with the cloud. This process ensures data persistence and enables continuous monitoring of parking utilization and visitor dynamics through remote access.

4. Experiments

To verify the effectiveness and applicability of the proposed system, an on-site experiment was conducted using camera footage recorded at the entrance and exit of a parking area in Shirakawa-go. The objectives were threefold: (1) to evaluate the system's recognition performance under real-world environmental conditions, (2) to analyse vehicle inflow–outflow tendencies and parking-stay durations, and (3) to demonstrate

Figure 3: Camera installation

the feasibility of data-driven management for small-scale tourist destinations.

4.1 Field installation and data collection

In June 2025, the authors deployed the proposed system at the Terao Temporary Parking Area in Shirakawa-go. A network camera and a local processing computer were installed near the entrance to monitor both entry and exit. The camera was mounted beneath the roof of a nearby building and carefully adjusted to achieve a stable view of incoming and outgoing vehicles (Figure 3). The system utilized an AXIS P1465-LE infrared-compatible network camera (manufactured by AXIS Communications, Sweden), which ensured stable image quality in both daytime and nighttime conditions. The camera settings, such as brightness and focal distance, could be remotely adjusted through a browser-based interface. Its 2.73 × optical zoom function was used during installation to adjust the framing and improve license plate readability.

Captured video streams were processed locally on an edge device running the YOLOv8-based detection and recognition modules. Recognition results were automatically structured into CSV files and uploaded to the cloud for long-term storage and analysis. This configuration allowed continuous, unattended operation and enabled stable collection of vehicle data.

4.2 On-site evaluation of recognition performance

To evaluate the recognition performance under field conditions, a qualitative analysis was performed using image frames captured at the site. As shown in Figure 4 (left), the license plate of an incoming vehicle—originally Nagoya 508 tsu 8576—was successfully detected. The model correctly recognized the numeric and hiragana portions (508, tsu, 8576) but misclassified the region name Nagoya as Kyoto. In Figure 4 (right), where the vehicle approached from a more oblique angle, only the lower four digits (9282) were correctly recognized. These examples demonstrate that recognition accuracy is influenced by the wide variety of environmental factors in real-world conditions, such as illumination, plate tilt, and partial occlusion. The findings suggest that, while the proposed end-to-end model performs robustly overall, further accuracy improvements could be achieved through temporal smoothing, multi-frame fusion, and adaptive image-enhancement techniques. Such refinements will be explored in future work to enhance recognition stability under challenging conditions.

4.3 Analysis of vehicle flow and parking behaviour

Using the collected time-series data, the study further examined the applicability of the proposed system for data-driven tourism management. Figure 5 illustrates the daily inflow and outflow of vehicles from July 10 to July 31, 2025, revealing clear distinctions between weekdays and weekends. Traffic peaks were observed during weekends, enabling local managers to identify specific days of high congestion.

Figure 6 illustrates the hourly vehicle inflow and outflow during the three-day holiday period from July 19 to 21, 2025. On the first day (Saturday), visitor arrivals were concentrated between 10:00 and 11:00 a.m., with a secondary increase observed around 2:00 p.m. On Sunday, the total number of visitors further increased, and the peak inflow shifted earlier to around 9:00 and 10:00 a.m. Vehicle arrivals remained relatively high around 3:00 p.m., indicating continued inflow even in the late afternoon, while the main outflow peak occurred around 4:00 p.m., similar to the previous day. On the final day (Monday, Holiday), the overall number of visitors slightly decreased, and the departure peak appeared earlier in the afternoon, around 2:00 p.m. Furthermore, the inflow and outflow data enable the estimation of real-time parking occupancy at the site. Figure 7 illustrates the parking status on August 2 (Saturday) at the Terao Temporary Parking Area, which has a total capacity of 420 vehicles. The black line represents the number of parked vehicles, while the gray line indicates the number of available spaces. On this day, the number of parked vehicles reached its peak of 176 around 12:40 p.m., with the minimum number of available spaces being 244.

These patterns demonstrate clear temporal variations in vehicle movement across consecutive holidays, reflecting differences in travel behaviour and stay duration among tourists. Such analytical results can serve as valuable references for traffic guidance, store operating-hour adjustments, and the development of dynamic parking management strategies to improve congestion mitigation and overall visitor flow efficiency.

Figure 4: Example video frame showing a vehicle entering the parking area

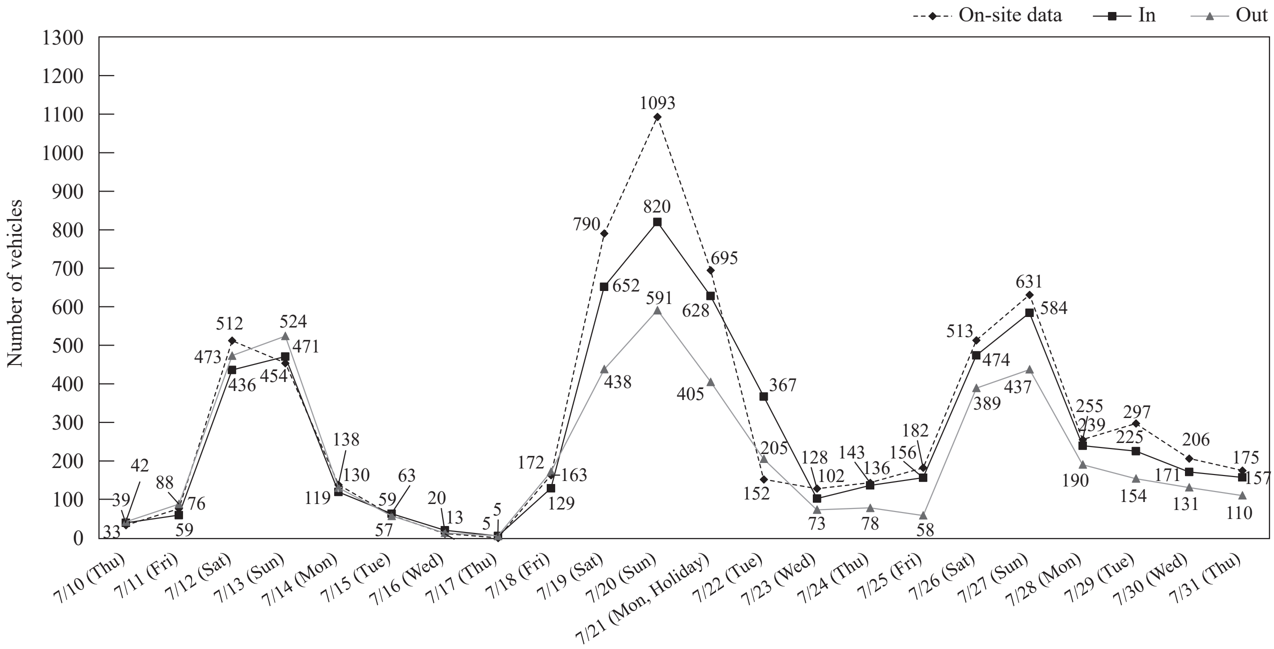

Figure 5: Daily vehicle inflow–outflow trends at Shirakawa-go from July 10 to 31, 2025

4.4 Camera distance adjustment experiments

Based on the results presented in Section 4.2 and Section 4.3, one potential factor contributing to reduced LPR accuracy was identified as camera-to-vehicle distance. The AXIS P1465-LE camera, limited to a 2.73× optical zoom and mounted beneath the building roof, faced restrictions in both viewing angle and height. As a result, license plates appeared relatively small within the captured frames, and the combination of motion blur, illumination variations, and long-range imaging occasionally made character recognition difficult.

To investigate this issue quantitatively, the authors conducted an additional field experiment in August 2025, relocating the camera closer to the parking-lot entrance and exit (Figure 8). In the initial setup, the camera was installed approximately 20 m from the point where vehicles were captured. In the adjusted configuration, the distance was reduced to roughly 10 m, and the installation height was lowered to about half of its original value.

The cropped license plate images obtained at this distance were approximately twice the width and height of those captured from the original position. All attributes of the license plates shown in Figure 9, including the region name, numbers, and hiragana, were correctly recognized. These findings provide useful insights for optimizing camera placement and equipment configuration in future deployments.

5. Results and discussion

Based on the field experiment described in Section 4, this section presents the quantitative and qualitative results obtained from the deployed system and discusses their implications for sustainable tourism management.

5.1 Quantitative evaluation of recognition performance

The proposed YOLOv8-based model achieved a precision of 0.7983, recall of 0.6926, mean average precision (mAP@0.5) of 0.7726, and mAP@0.5–0.95 of 0.614. These metrics indicate that the model maintains a favourable balance between recognition accuracy and computational efficiency. The results demonstrate that the custom-trained model can reliably detect vehicles and recognize license plates under diverse lighting and background conditions.

5.2 Qualitative analysis and environmental factors

During the field operation, the system processed approximately 35,758 unique vehicles, corresponding to over 70,000 individual passage events at the entrance and exit. The system operated continuously without interruption and maintained stable performance under typical outdoor conditions. However, recognition accuracy was occasionally influenced by motion blur, long camera-to-vehicle distance, or oblique viewing angles. Comparative experiments adjusting the camera installation height and distance confirmed that enlarging the license plate region within the captured frame significantly improved recognition accuracy. These results suggest that optimizing camera placement, particularly with respect to angle and distance, is a critical factor for achieving reliable recognition performance. Future enhancements, such as adopting higher-zoom cameras or integrating temporal smoothing and multi-frame fusion, are expected to further improve the robustness of license plate recognition in real-world environments.

5.3 Analysis of vehicle flow and behavioural patterns

Using the time-series data collected over several weeks, vehicle inflow and outflow patterns were analysed to examine

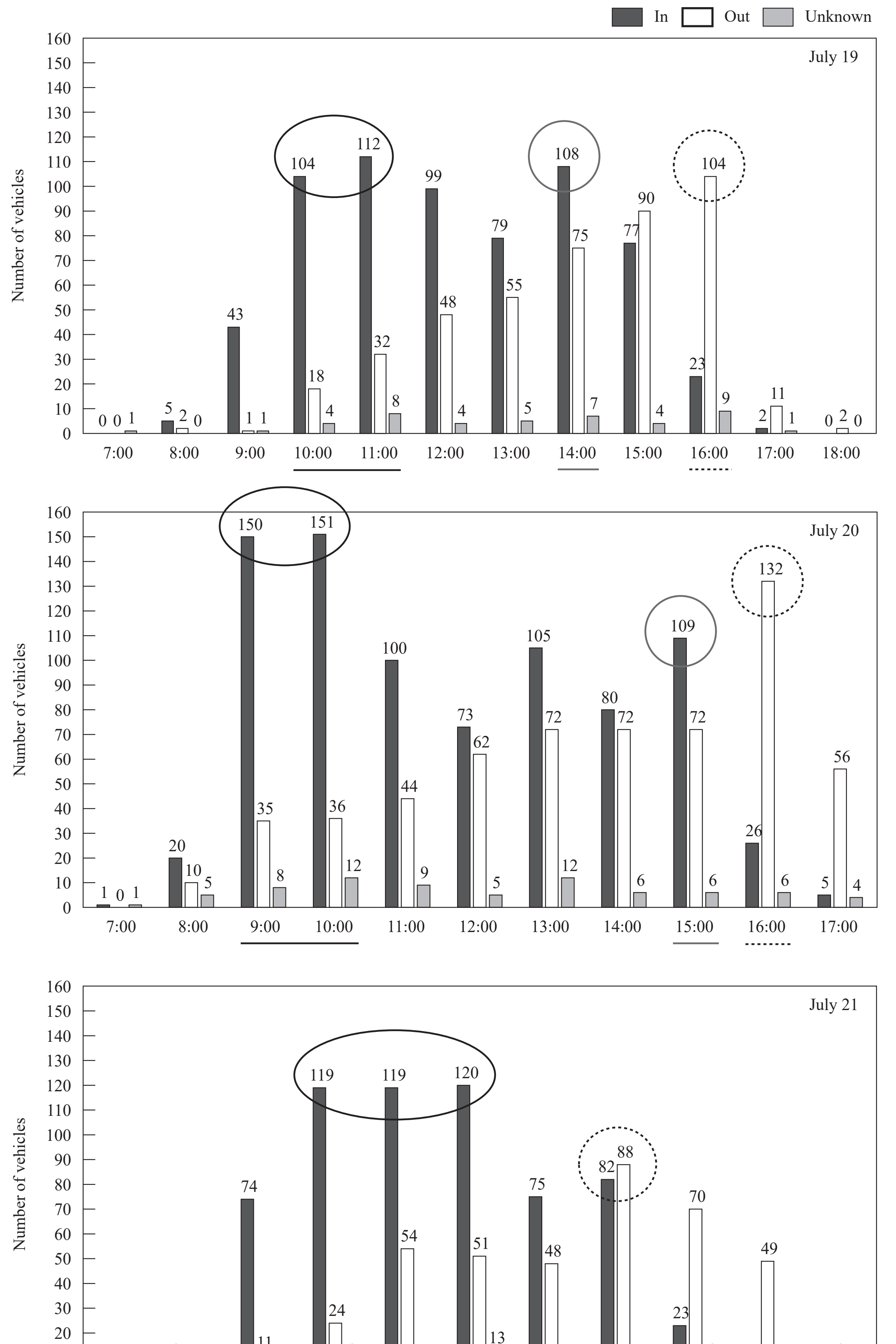

Figure 6: Hourly vehicle inflow and outflow during the three-day holiday period from July 19 to 21, 2025

Note: "In" denotes entering vehicles; "Out" denotes exiting vehicles; "Unknown" refers to cases where entry/exit direction could not be identified from the frame.

Date	8/2 (Sat)
On-site data	471
In	430
Out	399

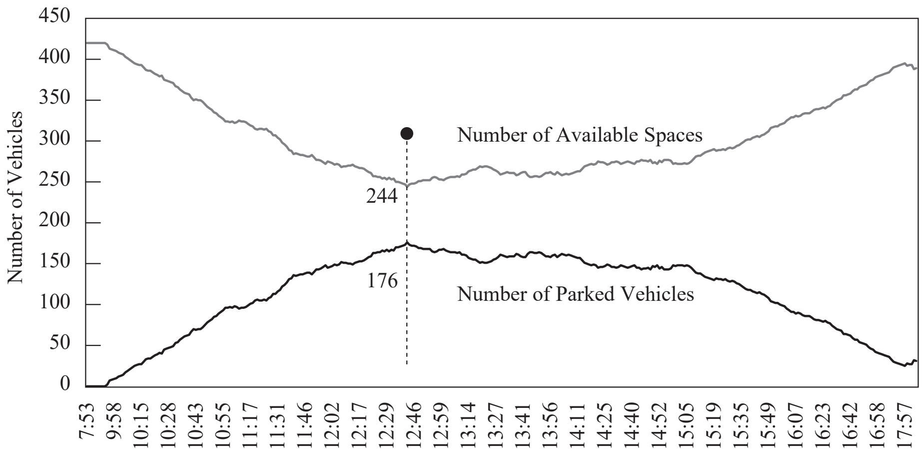

Figure 7: Parking occupancy and available spaces at the Terao temporary parking area on August 2 (Sat)

Figure 8: Camera position after repositioning closer to the traffic lane

Figure 9: Recognition results at different camera distances

the system's applicability to data-driven destination management. In the local operation context, manually recorded data were available only as daily aggregates. By contrast, the proposed LPR system enables the collection of vehicle inflow and outflow data at much finer temporal granularity, allowing a more detailed examination of hourly behavioural patterns.

The time-series analysis presented in Section 4.3 revealed clear temporal variations between weekdays and weekends, reflecting behavioural differences in visitor arrival, departure, and parking occupancy patterns. Feedback from Mr. Yamada, Director of the Shirakawa-go World Heritage Site Gassho Style Preservation Trust, emphasized that the developed system is expected to contribute to optimizing parking staff allocation, improving traffic guidance, and supporting dynamic pricing strategies. Moreover, the aggregated count data can serve as foundational input for simulation and forecasting models, including those for real-time congestion prediction.

A comparison between LPR-derived counts and manually recorded data indicated that the deviation in daily vehicle totals generally remained within approximately 10 to 20 percent. Importantly, this level of discrepancy did not alter the identification of key behavioural patterns such as peak visitation hours or weekday–weekend differences. These findings suggest that, despite occasional OCR errors at the plate level, the system provides sufficiently accurate data for analysing temporal variations in tourist dynamics and for supporting practical decision-making in parking and tourism management.

5.4 Cost considerations and practical feasibility

To illustrate the feasibility of implementing the proposed system in rural destinations, we provide an approximate cost range. The initial installation, including a network camera and an edge-processing computer, required on the order of 300,000-400,000 JPY, which is substantially lower than the 2-3 million JPY range quoted by commercial vendors for similar vehicle-counting systems.

Operational costs in Shirakawa-go further highlight the relevance of automation. Staffing for parking areas and shuttle-bus operations typically requires several personnel, and the combined labor and operation costs can reach several hundred thousand yen per day, even on days with unexpectedly low visitor turnout. These comparisons indicate that the proposed system represents a significantly more cost-effective and sustainable solution for small municipalities compared with manpower-dependent methods or large-scale ITS installations.

6. Conclusion

This study developed and implemented an AI-based License Plate Recognition (LPR) system for analyzing tourist dynamics in Shirakawa-go, a UNESCO World Heritage site in Japan. The proposed system successfully enabled automated and continuous data collection on visitor behaviour, including vehicle origin, stay duration, and rental car usage. Unlike conventional manual counting or survey-based methods, the system allows long-term monitoring with minimal human intervention, creating a valuable dataset for evidence-based policymaking.

The findings demonstrate that such AI-driven sensing systems can effectively support overtourism mitigation, parking optimization, and sustainable resource management in small-scale heritage destinations. Moreover, they highlight the potential of intelligent data-collection frameworks to enhance smart destination management, particularly for local governments facing constraints in budget and manpower.

Although the system achieved reasonable accuracy, several limitations remain, particularly in handling ambiguous or uncertain recognition cases caused by strong backlighting, motion blur, or partial occlusion. To address these challenges, future work will explore the integration of a local Large Language Model (LLM) as a post-processing and reasoning layer. A locally deployed LLM can analyse recognition confidence, temporal consistency, and contextual metadata to infer the most plausible license plate outputs in uncertain situations [AlDahoul et al., 2025]. This hybrid framework, combining deep learning for perceptual recognition and LLM for contextual reasoning, is expected to improve overall precision, reduce false detections, and enhance system interpretability. Furthermore, operating the LLM locally ensures data privacy and compliance with regional regulations, which is essential for real-world deployment in public spaces. In future studies, the research team also plans to integrate the system with multimodal data sources, such as pedestrian flow and public transportation records. Through these efforts, the project aims to advance the realization of smart and sustainable tourism ecosystems, leveraging AI technologies to balance visitor experience, operational efficiency, and community well-being.

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References

AlDahoul, N., Tan, M. J. T., Tera, R. R., Karim, H. A., Lim, C. H., Mishra, M. K., and Zaki, Y. (2025). Multitasking vision language models for vehicle plate recognition with Vehicle-PaliGemma. *Scientific Reports*, Vol. 15, 26189.

Bian, M., Yamada, H., and Fukuyasu, M. (2025). Audio guide system for smallscale historical buildings. *Journal of Global Tourism Research*, Vol. 10, No. 1, pp. 41-52.

Gao, Y., Mu, S., and Xu, S. (2024). Toward unified end-to-end license plate detection and recognition for variable resolution requirements. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 25, No. 9, pp. 10689-10701.

Japan National Tourism Organization (2025). *Estimated number of inbound tourists to Japan in April 2025* (Retrieved October 21, 2025 from https://www.jnto.go.jp/statistics/data/_files/20250521_1615-1.pdf). (in Japanese)

Jocher, G., Chaurasia, A., and Qiu, J. (2023). *Ultralytics YOLOv8* (Retrieved October 21, 2025 from https://github.com/ultralytics/ultralytics).

Rajesh, P., Kallakuri, D., Chagarlamudi, S., Vissavajhula, S. M., Meng, J., and Zhao, J. (2025). Intelligent parking guidance system using computer vision, IoT, and edge computing. *IEEE Open Journal of Intelligent Transportation Systems*, Vol. 6, pp. 1185-1199.

Roboflow Universe, Number Plate in Japan Computer Vision Model (2025). *Number plate in Japan computer vision model* (Retrieved October 21, 2025 from https://universe.roboflow.com/moriken/number-plate-in-japan).

Shirakawa Village (2025). *Tourism statistics of Shirakawa Village* (Retrieved October 21, 2025 from https://www.vill.shirakawa.lg.jp/1260.html). (in Japanese)

Sonnara, F., Chihaoui, H., and Filali, F. (2025). Efficient real-time license plate recognition. using deep learning on edge devices. *Journal of Real-Time Image Processing*, Vol. 22, No. 159, pp. 1-15.

Tang, J., Wan, L., Schooling, J., Zha, P., Chen, J., and Wei, S. (2022). Automatic number plate recognition (ANPR) in smart cities: A systematic review on technological advancements and application cases. *Cities*, Vol. 129, 103833.

Tu, Y., Urata, M., Endo, M., and Yasuda, T. (2022). Proposals and practices for open image data processing and promotion in local governments. *2022 IEEE 11th Global Conference on Consumer Electronics*, pp. 496-500.

Zou, Z., Chen, K., Shi, Z., Guo, Y., and Ye, J. (2023). Object detection in 20 Years: A survey. *Proceedings of the IEEE*, Vol. 111, No. 3, pp. 257-276.

Zubiaga, M., Izkara, J. L., Gandini, A., Alonso, I., and Saralegui, U. (2019). Towards smarter management of overtourism in historic centres through visitor-flow monitoring. *Sustainability*, Vol. 11, 7254.

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