General Article

Development of pedestrian count prediction and its pilot implementation for local tourism-related businesses

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Abstract

The increasing availability of human mobility data—enabled by AI-based cameras or mobile GPS technologies—has made it easier to monitor pedestrian activity in tourist destinations. However, practical applications that directly support business operations remain limited. This study develops a pedestrian count prediction model as a concrete approach to data utilization that goes beyond simple descriptive monitoring. Using pedestrian count data collected by AI cameras installed in a shopping district in Takayama City, Gifu Prefecture, we constructed a prediction AI model that incorporates weather conditions and local event information. The resulting forecasts were provided to a stationery shop and a restaurant in the tourist area in the form of an hourly prediction calendar by a communication chat tool and email. Businesses reported that the availability of quantitative forecasts not only enabled more appropriate staffing, which had previously relied heavily on intuition, but reduced the burden of staff scheduling, contributing to reductions in unnecessary labor costs. These findings demonstrate that pedestrian count prediction and our user interface can effectively support operational efficiency and managerial decision-making for businesses in tourist destinations.

Keywords

data utilization, pedestrian count prediction, tourism area management, decision-making support, machine learning

1. Introduction

Japan is experiencing a rapid progression of population aging and declining birthrates [National Institute of Population and Social Security Research, 2023]. As a result, the shrinking working-age population and the accompanying labor shortage have become nationwide challenges [Ministry of Health, Labour and Welfare, 2025]. Under these increasingly severe conditions, achieving sustainable business operations requires not only traditional intuition and experience but also rational and efficient decision-making supported by data. A well known example is Ebiya, a retail shop located in Okage Yokocho, a tourist district in Ise City, Mie Prefecture. By utilizing data—most notably customer traffic forecasts—the shop successfully reduced food waste, optimized staff allocation, and achieved both increased sales and improved operational efficiency [Small and Medium Enterprise Agency, 2019]. This case demonstrates that data utilization can significantly contribute to business improvement for operators facing labor shortages.

For the tourism industry, which relies on visitors who physically travel from outside the region, fluctuations in customer traffic—represented by human mobility and pedestrian counts—constitute essential baseline data that underpin inventory management and staff scheduling [Hori et al., 2023]. Recent advancements in AI based camera technologies and the widespread availability of mobile GPS data have dramatically reduced the cost of collecting human mobility data in tourist areas, making it easier to accumulate detailed data. However, transforming these large volumes of accumulated data into actionable managerial decisions still often requires advanced expertise. For small local businesses with limited resources, there is a pressing need for systems that allow users without specialized knowledge to intuitively understand data and translate it into concrete decision making.

2. Positioning of this study

Several domestic and international cases demonstrate the use of pedestrian data in tourism management. In Japan, Ebiya in Ise City has achieved notable results—including reduced waste, improved staff efficiency, and increased sales—through data-driven customer traffic forecasting [Small and Medium Enterprise Agency, 2019]. Kyoto City has developed the “Kyoto Tourism Comfort Map,” which uses AI to predict congestion levels and encourage the spatial distribution of visitors [Kyoto City Tourism Association, n.d.]. Internationally, Dubrovnik, Croatia, operates the “Respect the City” project, which integrates real-time pedestrian counts from AI cameras installed at the gates of the UNESCO-listed Old Town with cruise ship schedules to inform congestion control and entry restrictions [Camatti et al., 2020]. Venice, Italy, has established a “Smart Control Room”—a centralized operations hub—to tackle overtourism. This facility integrates multiple sensors and mobile phone data to estimate real-time pedestrian counts and forecast future trends [City of Venice, 2023]. Amsterdam, the Netherlands, operates the “Public Eye” project, which uses municipal cameras and AI to estimate congestion levels and movement directions in public spaces. This enables city officials to perform crowd management (e.g., crowd dispersal, one-way traffic measures) and provides real-time crowdedness information to residents and visitors via apps, websites, and digital kiosks [International Telecommunication Union, 2021].

Despite these advancements, common limitations remain. The Ebiya case, while pioneering, is limited to a single store and does not provide a scalable forecasting system accessible to non-experts across a region. The cases in Kyoto, Dubrovnik, Venice, and Amsterdam primarily focus on macro-level objectives such as visitor information, entry control, and city-wide congestion management. They do not directly support micro-level managerial decisions—such as daily inventory planning or staff scheduling—required by local businesses.

Given that small and medium-sized enterprises (SMEs) account for approximately 80 % of the tourism industry [World Economic Forum, 2025], forecasting tools tailored to the practical needs of such businesses without data-analysis expertise have significant potential. Moreover, academic knowledge remains limited regarding how data-driven forecasts influence managerial decision-making and how the business owners feel to them. The sustainability of tourist destinations depends on the efficient management of local businesses, and enabling operators to optimize their operations based on human mobility data is essential for maintaining regional competitiveness. Establishing an environment in which businesses can routinely use such forecasts in daily decision-making is therefore critically important.

This study focuses on "small-scale businesses," which face particularly severe resource constraints among SMEs. We develop and provide pedestrian count predictions tailored to these local small businesses and empirically examine their usefulness and challenges for social implementation. The novelty of this study lies in constructing a pedestrian count prediction optimized for business use by leveraging locally collected pedestrian data. Through pilot implementation in actual stores and workshops with local businesses, we evaluate not only technical accuracy and managerial effects but also how such people feel to the prediction such as increased confidence and reduced stress in decision-making, and the broader acceptability of the system.

3. Background and prior efforts

The authors have collaborated with Takayama City, local tourism businesses, and NEC Solution Innovators, Inc. to collect and utilize pedestrian and vehicle traffic data. In 2021, AI cameras were installed in major tourist areas of Takayama, enabling 24/7 pedestrian counting (Figure 1) [Hori et al., 2023]. The data collected through this system have played a crucial role in visualizing local pedestrian trends—previously understood only through experience and intuition—as objective numerical information, thereby contributing to situational analysis for tourism policy and the understanding of human mobility.

While the accumulated pedestrian count data are highly effective for accurately understanding past trends, the authors aimed to further utilize these data to generate pedestrian count

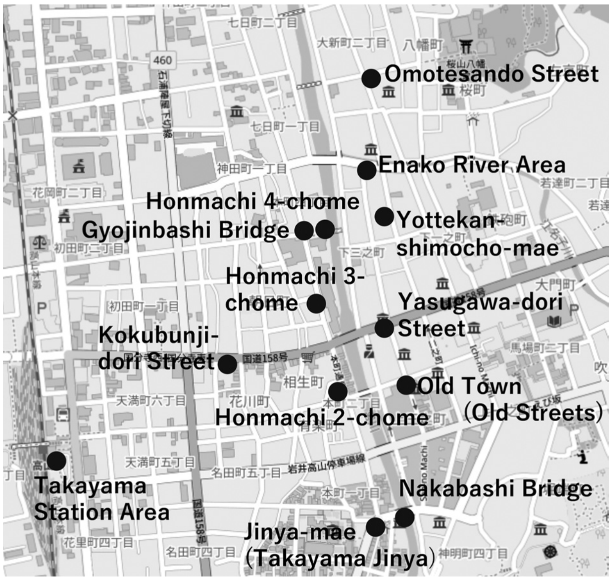


Figure 1: Locations of installed AI cameras

Note: ● AI camera Locations.
Source: Created by author based on Hori et al., 2023; OpenStreetMap, 2026).

forecasts that could serve as decision-making materials for business operators. Simply knowing past data is insufficient for creating accurate staffing or procurement plans for the following days or the next month, especially when conditions change daily due to weather or scheduled events.

Interviews with local tourism-related businesses have revealed strong demand for more detailed pedestrian count predictions that directly support staff scheduling and perishable inventory management. Whereas public sector forecasting focuses on macro level congestion reduction, private businesses require micro level benefits such as avoiding economic losses through data supported decisions. Based on this background, we developed hourly and long term (two month) pedestrian count predictions tailored to the decision making of businesses in Takayama's main tourist district.

4. Development of pedestrian count predictions for local businesses

4.1 Model design

This study was guided by the principle of achieving both high accuracy predictions suitable for business decision making and low computational cost that enables sustainable operation within the region. For the prediction model, we adopted Prophet [Taylor and Letham, 2018], a time series model well suited for extracting periodic fluctuations, and LightGBM [Ke et al., 2017], a gradient boosting decision tree model capable of learning nonlinear factors with high speed and accuracy. The final prediction values were obtained through an ensemble method that simply averaged the outputs of the two models. Complex models such as deep learning were intentionally avoided in favor of computationally lightweight methods, so that the system would not depend on expensive computing resources (e.g., GPUs) and could be operated in real time within the typical information and communication environments of regional areas, while also allowing rapid deployment to other regions.

4.1.1 Data and feature engineering

The model was trained using pedestrian count data collected by AI cameras, which has been accumulated since August 2021. Considering that the data collection periods vary depending on the camera locations and to ensure the stability of the dataset, this study utilized data from January 1, 2023, up to the day before the prediction was generated for the training phase.

To further improve prediction accuracy, we defined external factors specific to Takayama City as additional features. Specifically, in addition to major national holiday periods (e.g., Golden Week, Obon), we incorporated local event information as dummy variables such as Takayama Festival, fireworks displays, night markets, or Bon dances, based on consultations with the city and the Hida Takayama Tourism & Convention Bureau.

To capture temporal periodicity, sine and cosine transformations were applied to represent cycles at the hourly, daily, weekly, monthly, and annual levels (accounting for leap years), extracting variables with periodic characteristics. Furthermore, weather and temperature data obtained from Japan Meteorological Agency's official website were integrated [Japan Meteorological Agency, 2026]. Social dynamics such as "COVID 19 State of Emergency declarations" and the operating hours of the Morning Market, a major tourist attraction, were also included as features, enabling the model to capture a wide range of factors influencing pedestrian fluctuations.

4.1.2 Training procedure and parameter settings

To ensure reproducibility, the hyperparameters and training processes for each algorithm were configured as follows.

- Training with Prophet:
  To optimize the model for hourly data, the seasonality mode was set to multiplicative. In addition to the default settings, we defined additional seasonality: hourly (Fourier order 3), daily (order 6), and weekly (order 3). The changepoint_prior_scale was set to 0.5 to allow moderate flexibility in trend changes. For exogenous variables such as local events, the prior_scale was set to 100 to ensure that the model strongly learned the influence of specific events on pedestrian activity.
- Training with LightGBM:
  Considering that patterns of variation differ significantly across seasons and social conditions, the entire training dataset was divided into four periods: December to March 15, March 16 to May, June to July, and August to November. Within each period, the data were further segmented into "weekdays," "holidays," and "special event periods" (e.g., Golden Week, Takayama Festival), and training and prediction were conducted separately for each segment. Key parameters were set to max_depth = 5, num_leaves = 31, and learning_rate = 0.1, balancing the need to suppress overfitting while capturing localized fluctuations.

4.1.3 Post-processing and categorization

As a post processing step to ensure practical usability, predicted values for nighttime and early morning hours (22:00-5:00) were clipped to zero. Additionally, the continuous predicted pedestrian counts were converted into a 20 level "congestion index" to facilitate intuitive understanding by business operators.

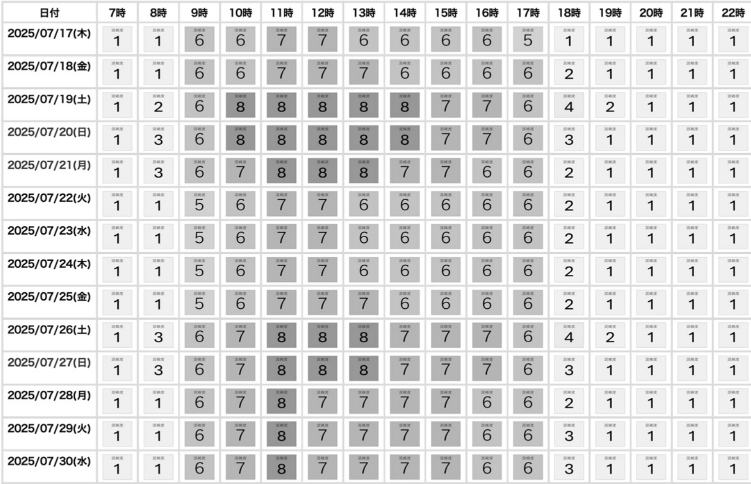
The boundaries for the congestion levels were defined as follows. First, based on historical pedestrian data, the peak hours during the Takayama Festival, when the highest annual pedestrian volumes are observed, were assigned to level 20, while late night hours with extremely low pedestrian activity were assigned to level 1. Next, the mean value of all data excluding these extremes was calculated and used as the midpoint boundary between levels 10 and 11. Finally, the interval between the level 1-2 boundary and the mean, as well as the interval between the mean and the level 19-20 boundary, were each evenly divided to determine the boundaries for all remaining levels.

This method allowed the visualization of subtle fluctuations of weekday demand that would be difficult to distinguish using simple equal interval segmentation, while also enabling intuitive explanations grounded in local experience—for example, "a congestion level of 20 corresponds to the spring Takayama Festival." In this way, the approach balanced quantitative rigor with the practical interpretability required by on site business operators.

4.2 User Interface for decision support

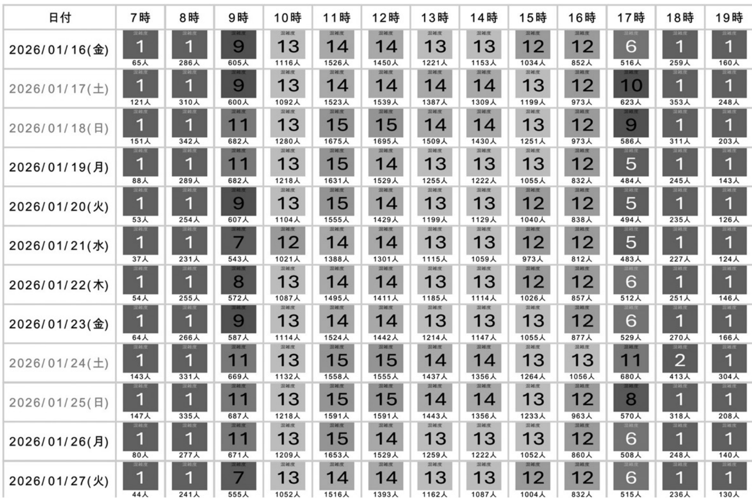
To enable business operators to apply the output of the developed pedestrian count forecasts to concrete managerial decisions, an intuitive user interface (UI) was designed. While congestion information for tourists is typically presented using coarse categories of three to five levels, this study defined a more fine grained congestion level to support precise managerial decisions such as determining whether an additional staff member is needed. The forecasts were visually presented using color coding, and an initial prototype with ten levels was created (Figure 2).

However, through pilot implementation in participating stores and subsequent interviews, it became clear that the ten level scale lacked sufficient resolution for daytime congestion levels, which are crucial for managerial decisions. Specifically, the ten level forecasts tended to group weekday daytime periods into the same congestion category, making it inadequate for adjusting staff schedules based on subtle day to day variations in demand. In response to requests from business operators who wanted "more detailed information on fluctuations in pedestrian numbers," the resolution was refined to better align



日付	7時	8時	9時	10時	11時	12時	13時	14時	15時	16時	17時	18時	19時	20時	21時	22時
2025/07/17(木)	1	1	6	6	7	7	6	6	6	6	5	1	1	1	1	1
2025/07/18(金)	1	1	6	6	7	7	7	6	6	6	6	2	1	1	1	1
2025/07/19(土)	1	2	6	8	8	8	8	8	7	7	6	4	2	1	1	1
2025/07/20(日)	1	3	6	8	8	8	8	8	7	7	6	3	1	1	1	1
2025/07/21(月)	1	3	6	7	8	8	8	7	7	6	6	2	1	1	1	1
2025/07/22(火)	1	1	5	6	7	7	6	6	6	6	6	2	1	1	1	1
2025/07/23(水)	1	1	5	6	7	7	6	6	6	6	6	2	1	1	1	1
2025/07/24(木)	1	1	5	6	7	7	6	6	6	6	6	2	1	1	1	1
2025/07/25(金)	1	1	5	6	7	7	7	6	6	6	6	2	1	1	1	1
2025/07/26(土)	1	3	6	7	8	8	8	7	7	7	6	4	2	1	1	1
2025/07/27(日)	1	3	6	7	8	8	8	7	7	7	6	3	1	1	1	1
2025/07/28(月)	1	1	6	7	8	7	7	7	7	6	6	2	1	1	1	1
2025/07/29(火)	1	1	6	7	8	7	7	7	7	6	6	3	1	1	1	1
2025/07/30(水)	1	1	6	7	8	7	7	7	7	6	6	3	1	1	1	1

Figure 2: Ten-level pedestrian count forecast calendar



日付	7時	8時	9時	10時	11時	12時	13時	14時	15時	16時	17時	18時	19時
2026/01/16(金)	1 65人	1 286人	9 605人	13 1116人	14 1526人	14 1450人	13 1221人	13 1153人	12 1034人	12 852人	6 516人	1 259人	1 160人
2026/01/17(土)	1 121人	1 310人	9 600人	13 1092人	14 1523人	14 1539人	14 1387人	14 1309人	13 1199人	12 973人	10 623人	1 353人	1 248人
2026/01/18(日)	1 151人	1 342人	11 682人	13 1280人	15 1675人	15 1695人	14 1509人	14 1430人	13 1251人	12 973人	9 586人	1 311人	1 203人
2026/01/19(月)	1 88人	1 289人	11 682人	13 1218人	15 1631人	14 1529人	13 1255人	13 1222人	13 1055人	12 832人	5 484人	1 245人	1 143人
2026/01/20(火)	1 53人	1 254人	9 607人	13 1104人	15 1555人	14 1429人	13 1199人	13 1129人	12 1040人	12 838人	5 494人	1 235人	1 126人
2026/01/21(水)	1 37人	1 231人	7 543人	12 1021人	14 1388人	14 1301人	13 1115人	13 1059人	12 973人	12 812人	5 483人	1 227人	1 124人
2026/01/22(木)	1 54人	1 255人	8 572人	13 1087人	14 1495人	14 1411人	13 1185人	13 1114人	12 1026人	12 857人	6 512人	1 251人	1 146人
2026/01/23(金)	1 64人	1 266人	9 587人	13 1114人	14 1524人	14 1442人	13 1214人	13 1147人	13 1055人	12 877人	6 529人	1 270人	1 166人
2026/01/24(土)	1 143人	1 331人	11 669人	13 1132人	15 1558人	15 1555人	14 1437人	14 1356人	13 1264人	13 1056人	11 680人	2 413人	1 304人
2026/01/25(日)	1 147人	1 335人	11 687人	13 1218人	15 1591人	15 1591人	14 1443人	14 1356人	13 1233人	12 963人	8 570人	1 318人	1 208人
2026/01/26(月)	1 80人	1 277人	11 671人	13 1209人	15 1653人	14 1529人	13 1259人	13 1222人	13 1052人	12 860人	6 508人	1 248人	1 140人
2026/01/27(火)	1 44人	1 241人	7 555人	13 1052人	14 1516人	14 1393人	13 1162人	13 1087人	12 1004人	12 832人	6 515人	1 236人	1 130人

Figure 3: Twenty-level pedestrian count forecast calendar

with on site decision making needs. At the same time, concerns were raised that using continuous values or excessively fine segmentation could reduce visual clarity. Therefore, after consultation with the pilot stores, the scale was redefined into twenty levels, striking a balance between practical usability and visual readability.

For the display format, we adopted a calendar layout, which is familiar to business operators through their daily management routines. By defining congestion level 1 with blue tones and level 20 with red tones, and interpolating the intermediate levels with a color gradient, we ensured visibility that allows for an intuitive grasp of congestion conditions (Figure 3, Table 1).

The forecast period was extended from the initial one month range to two months to better match business operational cycles. Many businesses finalize part time staff schedules, product ordering, and holiday planning monthly, and a one month forecast was insufficient for making decisions that require looking ahead to the following month.

Regarding delivery methods, several options such as printed materials and social media were considered. After discussions with business operators, the forecasts were delivered via LINE, the most common social media in Japan, which allows daily checking on smartphones (Figure 4), and via email, which is

Table 1: Color codes for each congestion level

Congestion Level	Hex Color Code	Congestion Level	Hex Color Code
1	6A64AE	11	99D02C
2	5468AD	12	CDE52F
3	396BB0	13	FFF231
4	2B78B0	14	FFCB1F
5	1C86AE	15	FF9913
6	1FB3B3	16	FF6E2B
7	1AA28E	17	FC4E33
8	2DA380	18	FC3633
9	32A65D	19	FA344D
10	55A73B	20	ED3B6B

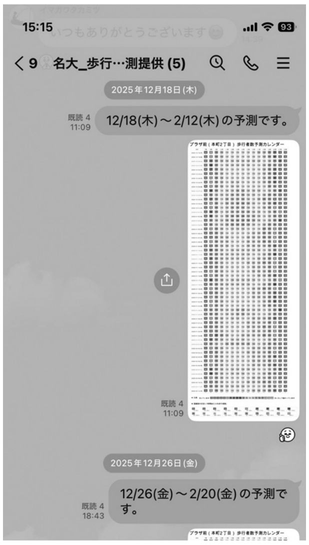


Figure 4: Forecast delivery via LINE

suitable for PC based management and printing. This combination enabled both quick in store confirmation and long term planning during administrative tasks.

In this way, by incorporating feedback from pilot stores during the development process, the system was designed so that non expert business operators could instantly understand forecasts for the coming days without requiring specialized data literacy, thereby enabling the optimization of concrete managerial decisions.

5. Evaluation and field implementation

5.1 Technical accuracy

To evaluate the validity of the developed prediction model, the agreement between predicted and observed pedestrian counts was assessed at eleven locations within the city. For evaluation, the predicted values were categorized into the twenty level congestion scale, and the Weighted Kappa coefficient was employed as the accuracy metric to measure the degree of agreement between predicted and observed values [Cohen, 1968]. The Weighted Kappa coefficient ranges from –1 to 1, where values closer to 1 indicate strong agreement, 0 indicates complete randomness, and –1 indicates complete disagreement. In this study, because the congestion levels constitute an ordinal scale with twenty categories, quadratic weights based on the squared distance between categories were applied to penalize larger misclassifications more heavily than smaller ones. According to the criteria of Landis and Koch, values above 0.8 are classified as “almost perfect,” indicating that the model maintains a sufficiently high level of accuracy for practical decision making [Landis and Koch, 1977].

To evaluate the model’s predictive performance over time, a rolling forecast evaluation was conducted. The model was first trained on data from January 1, 2023, to April 2024 and tested on May 2024. Subsequently, the training period was extended month by month, and the model was re-trained and tested on the following month’s data, continuing this process until No-

Table 2: Kappa coefficients for each location

Location	Kappa Coefficients
Yasugawa-dori Street	0.93
Nakabashi Bridge	0.88
Old Town (Old Streets)	0.84
Honmachi 2-chome	0.90
Kokubunji-dori-Street	0.78
Honmachi 4-chome	0.74
Yottekan-shimocho-mae	0.79
Omotesando Street	0.73
Jinya-mae (Takayama Jinya)	0.79
Honmachi 3-chome	0.87
Takayama Station Area	0.78
Average	0.82

Table 3: Average Kappa coefficients by season

Location	Spring (Mar-May)	Summer (Jun-Aug)	Autumn (Sep–Nov)	Winter (Dec-Feb)
Yasugawa-dori Street	0.95	0.93	0.95	0.88
Nakabashi Bridge	0.91	0.83	0.91	0.87
Old Town (Old Streets)	0.90	0.83	0.84	0.69
Honmachi 2-chome	0.90	0.89	0.91	0.90
Kokubunji-dori Street	0.80	0.76	0.79	0.74
Honmachi 4-chome	0.80	0.67	0.76	0.71
Yottekan-shimocho-mae	0.73	0.77	0.86	0.72
Omotesando Street	0.76	0.64	0.82	0.52
Jinya-mae (Takayama Jinya)	0.88	0.71	0.72	0.70
Honmachi 3-chome	0.87	0.84	0.90	0.84
Takayama Station Area	0.80	0.68	0.82	0.76
Average	0.84	0.78	0.84	0.76

vember 2025. The analysis of this integrated forecasting model, which combines the time-series capabilities of Prophet with the gradient boosting of LightGBM, revealed that the average hourly Cohen's kappa coefficient across all locations during the entire evaluation periods was 0.82, indicating high accuracy for a calendar-based forecasting model (Table 2). Seasonal trends revealed higher accuracy during spring and from August through November. In contrast, lower accuracy was observed during the rainy season (June-July) and winter (December–February) (Table 3).

5.2 Effects observed in individual stores

To examine the usefulness of the pedestrian count predictions, a pilot study was conducted with two stores located in the main tourist area of Takayama City, in which a two-month forecast calendar was provided once a week.

The first store was a stationery shop whose primary customers are tourists. The owner, in his thirties, is highly interested in data utilization and actively incorporates it into his operations. Three notable effects were observed in this store. The first was the "reassurance" gained by the owner through having objective forecast values. During on-site interviews, the owner repeatedly emphasized that "having the forecasts has given me a great sense of ease." The forecast calendar not only served as one of the concrete bases for decision-making but also had a positive psychological impact on the owner.

The second effect was qualitative improvement in managerial decision-making and cost reduction enabled by objective data. A concrete example was the optimization of staffing during the New Year period in 2025. Based on his experience, the owner had expected the New Year holidays to be extremely crowded and had been considering hiring additional temporary staff, as he did every year. However, the forecast values shown on the 10-level calendar provided at the time indicated lower than expected congestion, around level 4 (Figure 5). Trusting the forecast, the owner decided not to increase staffing, and he succeeded in reducing direct labor costs without compromising service quality. This demonstrates that having objective data as a foundation enables confident decision-making under uncertainty and provides relief for the owner.

The third effect was the organizational change in decision-making brought about by sharing the forecast information among staff. In this store, the forecast calendar was posted in a location accessible to all employees (Figure 6), allowing them to anticipate busy and quiet periods in advance. Consequently, staff members began making voluntary, data-driven suggestions such as "I will come to work on this day because it is expected to be busy" or "I would like to take a day off this week because the forecast shows it will be relatively quiet." This indicates that the pedestrian count predictions do not remain merely as decision-making material for the owner alone but also encourage cooperation among staff and promote autonomous operational optimization. The presence of a shared, ob-

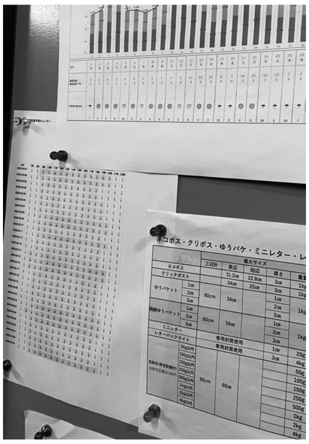


Figure 6: Forecast calendar displayed inside the store

日付	7時	8時	9時	10時	11時	12時	13時	14時	15時	16時	17時	18時	19時
2024-12-24	1	1	2	2	3	3	3	3	2	2	2	2	2
2024-12-25	1	1	2	3	3	3	3	2	2	3	2	2	2
2024-12-26	1	1	2	2	3	3	3	3	2	2	2	2	2
2024-12-27	1	1	2	2	3	3	3	2	2	2	3	2	2
2024-12-28	1	1	2	3	4	4	4	4	3	3	3	3	3
2024-12-29	1	2	3	3	4	4	4	4	3	3	3	3	3
2024-12-30	1	1	2	3	4	4	4	3	3	3	3	3	3
2024-12-31	1	1	2	3	4	4	4	4	3	3	3	3	3
2025-01-01	1	1	2	3	4	4	4	3	3	3	3	3	3
2025-01-02	1	1	2	3	4	4	4	4	3	3	3	4	3
2025-01-03	1	2	2	3	4	4	4	4	4	3	3	4	3
2025-01-04	1	1	2	3	4	4	4	4	3	3	3	3	3
2025-01-05	1	1	2	3	4	4	4	3	3	3	3	3	3

Figure 5: Forecast calendar provided at the New Year period in 2025

jective indicator makes consensus-building within an organization easier. The result demonstrates that the system can help shift management from relying solely on the owner's intuition to more strategic decision-making involving the entire workplace.

The second store was a restaurant operated by another owner in his thirties. With relatively high IT literacy and a proactive attitude toward data utilization, this owner used the forecasts in combination with his reservation data and existing accommodation statistics of the city. In this store, the forecasts were particularly valuable for decisions made more than a month in advance, such as staff scheduling and choosing which Thursday in a month to designate as the restaurant's monthly holiday. For example, when determining the regular holiday for January 2026, the owner compared the forecast values for the week of January 5, 2026, and the following week. After confirming that there was no significant difference between the two, he strategically designated the week of January 5, which coincided with the winter vacation period, as the holiday (Figure 7). This case illustrates that having data-based forecasts provided the owner with a sense of confidence and justification in choosing the holiday.

5.3 Evaluation of acceptance among local businesses

To clarify the acceptability of the developed pedestrian count prediction system in the context of social implementation, a questionnaire survey was conducted during a workshop involving local people in Takayama City (Figure 8). A total of 29 participants took part in the workshop, representing a diverse range of sectors: retail businesses (5 participants), service industries (5), municipal government staff (6), regional organizations and DMOs (2), financial and infrastructure-related companies (4), university students (1), and others (6). The age distribution of participants was also broad, including individuals in their teens (1), twenties (1), thirties (7), forties (7), fifties (6), sixties (5), seventies or older (1), and unknown (1), allowing the collection of opinions from both experienced business owners and next-generation participants.

Figure 8: Workshop with local people

The questionnaire used a five-point Likert scale (with 5 indicating the highest rating). In response to the question, "Would you like to use pedestrian count forecasts in your actual business operations?," the average score was 4.17, indicating a strong demand for such forecasts. For the question, "Do you think the accuracy of the forecast results is sufficient for practical business use?", the average score was 3.66, suggesting that, although the forecasts were viewed positively, business users may still expect higher accuracy. Regarding the evaluation of

日付	7時	8時	9時	10時	11時	12時	13時	14時	15時	16時	17時	18時	19時	20時	21時	22時
2025/12/26(金)	4 55人	6 96人	11 162人	12 267人	13 341人	14 375人	14 383人	14 371人	13 357人	13 354人	13 350人	13 292人	12 221人	11 145人	5 82人	2 0人
2025/12/27(土)	4 69人	8 118人	11 196人	13 319人	14 394人	14 437人	15 455人	15 465人	14 408人	14 392人	14 396人	13 306人	12 232人	11 165人	7 108人	4 0人
2025/12/28(日)	5 80人	11 136人	12 215人	14 368人	14 435人	15 466人	15 479人	15 486人	14 412人	14 373人	13 353人	12 267人	11 196人	11 134人	5 76人	2 0人
2025/12/29(月)	3 47人	7 102人	11 184人	13 330人	14 445人	15 496人	15 515人	15 517人	14 431人	13 343人	12 270人	11 195人	11 137人	5 76人	1 22人	1 0人
2025/12/30(火)	2 35人	6 99人	11 187人	13 336人	15 458人	15 512人	16 534人	16 548人	15 475人	14 406人	13 339人	12 252人	11 174人	7 111人	4 59人	2 0人
2025/12/31(水)	2 34人	5 80人	11 167人	13 302人	14 400人	15 462人	15 490人	15 495人	14 424人	13 352人	13 324人	12 246人	11 165人	6 89人	3 44人	1 0人
2026/01/01(木)	4 63人	8 118人	11 203人	13 311人	14 405人	15 473人	15 499人	15 507人	15 455人	14 421人	14 398人	13 311人	12 233人	11 165人	6 90人	3 0人
2026/01/02(金)	2 39人	7 114人	11 200人	13 320人	15 451人	16 535人	16 559人	16 561人	15 511人	15 447人	14 392人	13 303人	12 226人	11 152人	5 79人	3 0人
2026/01/03(土)	4 62人	11 145人	12 233人	14 367人	15 494人	16 574人	16 598人	16 601人	16 545人	15 492人	14 430人	13 339人	12 265人	11 187人	7 114人	5 0人
2026/01/04(日)	5 71人	11 150人	12 233人	14 367人	15 499人	16 549人	16 568人	16 567人	15 503人	14 429人	13 359人	12 268人	11 196人	10 124人	5 71人	2 0人
2026/01/05(月)	3 44人	6 89人	11 154人	12 259人	13 362人	14 393人	14 391人	14 381人	13 340人	13 305人	13 294人	11 199人	11 137人	6 86人	2 37人	1 0人
2026/01/06(火)	2 27人	5 77人	11 134人	12 211人	13 289人	13 319人	13 316人	13 309人	13 286人	12 256人	12 247人	11 188人	11 130人	5 81人	2 33人	1 0人
2026/01/07(水)	2 33人	5 79人	11 135人	12 211人	12 280人	13 307人	13 310人	13 301人	12 274人	12 253人	12 242人	11 198人	11 139人	6 90人	3 44人	1 0人
2026/01/08(木)	2 37人	5 83人	11 137人	11 204人	12 260人	13 285人	13 291人	13 289人	12 267人	12 245人	12 235人	11 195人	11 135人	6 86人	2 39人	1 0人
2026/01/09(金)	2 37人	5 81人	11 137人	12 206人	12 265人	13 287人	13 297人	13 297人	12 281人	12 263人	12 257人	12 213人	11 151人	7 104人	4 61人	2 0人
2026/01/10(土)	4 58人	7 113人	11 170人	12 236人	13 342人	14 398人	14 413人	14 420人	14 382人	14 371人	13 350人	13 291人	12 217人	11 150人	6 99人	4 0人
2026/01/11(日)	5 73人	11 134人	11 188人	13 288人	14 394人	14 437人	14 444人	14 444人	14 388人	13 357人	13 332人	12 259人	11 186人	10 124人	5 72人	2 0人
2026/01/12(月)	3 46人	7 106人	11 159人	12 258人	13 360人	14 403人	14 403人	14 408人	13 343人	13 293人	12 275人	12 213人	11 148人	6 87人	2 38人	1 0人
2026/01/13(火)	2 33人	5 80人	11 139人	12 222人	13 293人	13 317人	13 315人	13 303人	12 272人	12 254人	12 244人	11 196人	11 136人	6 87人	2 39人	1 0人
2026/01/14(水)	3 40人	6 86人	11 149人	12 242人	13 318人	13 341人	13 342人	13 328人	13 290人	12 271人	12 259人	12 211人	11 148人	6 98人	3 50人	1 0人
2026/01/15(木)	3 45人	6 89人	11 149人	12 240人	13 312人	13 328人	13 331人	13 321人	13 286人	12 266人	12 256人	12 208人	11 145人	6 97人	3 48人	1 0人
2026/01/16(金)	3 46人	6 89人	11 152人	12 248人	13 316人	13 329人	13 336人	13 327人	13 301人	13 286人	12 279人	12 225人	11 158人	7 112人	4 67人	2 0人

Figure 7: Pedestrian count forecast calendar for January 2026

the user interface, the question "Were the 20-level congestion index and its color scale (blue to red) easy to intuitively understand?" received an average score of 4.21, and "Was the layout of the calendar (arrangement of dates and time slots) easy to read?" received 4.07. These results indicate that the system's design enables intuitive understanding even for business operators without specialized knowledge in data utilization.

In response to the question on barriers to adoption, "If forecast data were provided starting tomorrow, what would be the biggest challenge (or concern) in using it in your business operations?" few participants cited hardware or infrastructure issues. Half of the respondents answered "no particular concerns." The remaining half, however, pointed to operational or organizational challenges, such as "how to interpret the predicted values and apply them to decision-making" and "whether staff members would cooperate with decisions based on the forecasts." These results suggest that, beyond simply providing the forecast, support for communication that helps integrate forecasts into organizational decision-making, as well as efforts to improve data literacy across the region, will be essential for successful social implementation.

6. Discussion

6.1 Balancing accuracy and practicality

In this study, we achieved highly accurate predictions with a weighted Kappa coefficient exceeding 0.8 by combining Prophet, which excels at capturing periodic patterns, with LightGBM, which is effective at learning nonlinear factors. A noteworthy aspect is that this level of accuracy was attained while minimizing computational load. Specifically, verification using a standard personal computer (MacBook Pro 13-inch with an Apple M1 chip and 8GB of memory) confirmed that the prediction calculation for one location was completed within one minute. The model architecture does not require high-performance computing resources or specialized hardware, allowing users to generate up-to-date forecasts on demand even within the typical information and communication technology (ICT) environments of regional cities. This feature reduces the barriers to implementation and alleviates constraints related to computational resources when expanding the system to other regions. For small businesses to sustainably adopt predictions provided by regional organizations, computational efficiency is a key practical requirement, given the typically limited budgets allocated to such services.

Additional data sources such as the number of overnight visitors in Takayama or the number of international arrivals at nearby airports could further enhance prediction accuracy. If such data could be integrated in real time on a daily basis, even greater accuracy could be expected. Therefore, the approach, machine learning models and readily available data, adopted in this study can be considered effective for social implementation at this stage, achieving a balance between practical computational load and high accuracy.

6.2 Requirements and psychological value of forecasts for business operators

Interviews conducted at the pilot stores revealed that forecasts for business operators offer three key types of value: alignment with practical operations, reassurance, and changes in organizational decision-making. For decisions directly related to costs and scheduling such as staff allocation and setting regular holidays, the high-resolution 20-level forecast and the two-month prediction adopted in this study were found to be essential requirements for practical use. Furthermore, insights gained from the stationery store case, such as the owner's increased confidence and sense of ease, suggest that forecasts serve not only as tools for operational efficiency but also play a role in reducing the burden of decision-making in the uncertain context of tourism management. Objective data can complement experience-based intuition, enabling more confident and assured decision-making. In addition, sharing the forecast calendar within the store allowed the forecasts to function as an objective, common reference point, prompting autonomous actions among staff, such as voluntary shift proposals. This demonstrates that pedestrian count forecasts do not remain merely as decision-making material for the owner alone, but also serve as an effective means of facilitating consensus-building and operational optimization across the entire store.

7. Conclusion

In this study, we developed a pedestrian count prediction system tailored to business decision-making, using AI camera data collected in Takayama City, Gifu Prefecture, and examined its usefulness from multiple perspectives. The results of the pilot implementation demonstrated that the lightweight, yet highly accurate forecasts generated through the combination of Prophet and LightGBM, together with the intuitive 20-level calendar-based user interface, were effective both in improving the management practices of small businesses and in reducing the psychological burden associated with decision-making. In particular, the way in which objective data fostered confidence among store owners and enabled optimal staffing during peak periods highlights the significance of this approach as a model case for sustainable data utilization in resource-constrained regions.

Future challenges include expanding the number of pilot stores and conducting quantitative evaluations to examine differences in usage patterns and effects across business types. Because rigorous operational impact assessments can be difficult for small stores, a phased expansion of participating businesses, combined with dissemination strategies that leverage positive user reviews and word-of-mouth, may help convey the value of the forecasts. Furthermore, beyond simply presenting forecast values, establishing a support system that bridges the gap between forecasts and concrete managerial decisions will be also essential for embedding data-driven management practices across the region. It is our hope that this study will contribute to improving sustainable working environments in tourist destinations and to further expanding data utilization efforts that leverage local resources.

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