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Demand Forecasting of Bento Considering the Product Popularity Estimation for Multiple Types of Bento Menus Using a Bayesian Rating System

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***Abstract*—"Bento," which refers to a single-portion, usually a meal packed in a box, is a widely accepted part of Japanese culture. In Japan, many companies produce and deliver bento. However, considerable food is wasted annually due to this service. Bento delivery service companies generally sell more than one type of menu item. In many cases, forecasters perform demand predictions manually based on their experience. Demand forecasting with high accuracy is challenging because quantifying the popularity of multiple types of bento menu items is difficult. This study proposes an algorithm consisting of two steps to forecast the demand for bento menu items. The first step in the algorithm is to quantify the popularity of products with multiple bento menu items. Product popularity is quantified with Bayesian estimation based on rating systems. The second step of the algorithm involves the use of machine learning to forecast demand, considering the popularity of products quantified in the first step. To demonstrate the usefulness of the proposed algorithm, numerical experiments are conducted with data provided by a bento delivery service company. With the proposed algorithm, forecasting is more accurate than with previous models. Additionally, the proposed algorithm exhibits higher accuracy than forecaster predictions for several evaluation indicators.**

***Index Terms*—Demand forecast, Rating system, Machine learning, Markov chain Monte Carlo sampling, Time-series data, Bayesian estimation.**

I. Introduction

RECENTLY, Japanese food culture has attracted worldwide attention. "Bento," which refers to a single-portion, usually a meal packed in a box, is a part of Japanese culture. Many companies in Japan offer takeout and food delivery services [1]. Food delivery, restaurant, and food-manufacturing industries in Japan waste 14.9 million tons food annually. Food losses due to overproduction and overordering amount to 2.02 million tons per year [2].

Bento delivery service companies require highly accurate demand forecasting models. Due to the short shelf life of bento, overestimating its demand can result in food waste. However, if demand is underestimated, customers' needs may not be satisfied. Bento delivery service companies sell multiple types of bento menu items. Traditionally, forecasters rely on intuition and experience to manually forecast demand to avoid food and opportunity losses. It is difficult to make accurate forecasts considering various factors effectively. Forecasts accuracy depend on the skills of the forecaster. A new forecaster requires time to become as accurate as an experienced one.

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Bento demand can be represented as a time series of sales data. In research on demand forecasting for time-series data, many methods have been proposed that utilize statistical models and machine learning [3], [4], [5]. However, few studies [6], [7] have conducted demand forecasting to account for product popularity. The previous method [6] could not consider the product popularity of multiple types of bento menu items. The other method proposed [7] is not applicable owing to issues caused by the type of data in the bento delivery service.

In this study, a demand forecasting algorithm was proposed utilizing a rating system based on Bayesian estimation and machine learning. Numerical experiments were conducted using real data provided by a company that manufactures and delivers bento. We compared the prediction accuracy with that of a previous model [6] to validate the usefulness of the proposed algorithm. Additionally, we compared the accuracy of the demand forecaster predictions with that of the proposed algorithm.

The originality of this study is that multiple types of bento menu items can be quantified. In the previous model [6], it was only possible to quantify the popularity of a single bento menu item. We consider that products with similar estimated popularity are virtually identical.

The remainder of this paper is structured as follows. Section II describes previous research on demand forecasting and issues in previous models. Section III outlines the proposed algorithm. Section IV presents details of the proposed algorithm. In Section V, we discuss numerical experiments conducted using real data from a bento delivery service company. Finally, in Section VI, we summarize the study and discuss future research tasks.

II. Related Research and Issues in Previous Models

A. Related Research

A number of studies have been conducted on demand forecasting. Statistical models and machine learning are the most common methods used in previous studies. Recently, integrated models that combine two or more models have been proposed.

Arunraj et al. [3] developed a forecasting method based on statistical modeling. They adopted the seasonal autoregressive integrated moving average with exogenous factors (SARIMAX) model to forecast demand for perishable food products. They showed that the SARIMAX model, which incorporates external factors such as price reduction and holiday effects, has better forecasting accuracy than the SARIMA model.

Dairu et al. [5] proposed a predictive model based on machine learning. They presented a forecasting model with gradient boosting to predict supermarkets' sales volumes. They compared the accuracy of the constructed method with those of linear and ridge regressions. They demonstrated that their proposed method achieved the best accuracy.

Punia et al. [4] developed a forecasting model that combined two or more models. They constructed a hybrid model combining random forest (RF) and long-short-term memory (LSTM) to forecast sales volume. They compared the accuracies of the proposed method, neural networks, LSTM, and RF. They showed that the hybrid model was the most accurate.

Ota et al. [6] and Woltmann et al. [7] presented demand forecasting models that considered the popularity of products. Ota et al. [6] quantified product popularity with a product popularity estimation model based on Bayesian estimation. They proposed demand forecasting models based on machine learning that consider the popularity of a product. Woltmann et al. [7] used a natural language processing to quantify the influence (popularity) of words on product descriptions. They proposed a demand-forecasting model that considers product popularity and calendar effects to forecast school cafeterias. Comparing the accuracy of predictions made using gradient boosting, support vector regression, and neural networks, they showed that the gradient boosting model was the most accurate.

B. Issue in Previous Models

The method developed by Ota et al. [6] was inadequate for quantifying the popularity of bento delivery services. Their method could not quantify the product popularity of multiple bento menus type. In order to accurately forecast demand, the product popularity of bento menus sold simultaneously should be quantified.

The method proposed by Woltmann et al. [7] is challenging for the quantification of product popularity in bento delivery services. They built a model to quantify product popularity from product descriptions with natural language processing. Bento delivery services generally do not have descriptions of bento menu products.

Other studies [8], [9] have been conducted on predicting popularity, although these methods are inadequate for quantifying product popularity in bento delivery services. For example, Trzciski et al. [8] built a model for predicting the number of views of a video, assuming the number of views of a video as its popularity. Mehrizi et al [9] proposed a Poisson regression model predicting the number of accesses in a network, assuming the number of accesses to the content to be the popularity.

III. Outline of The Proposed Algorithm

The algorithm proposed in this study is as follows:

STEP 1: Quantify the popularity of a bento menu item on which different products are sold daily.

STEP 2: Quantify the popularity of bento menu items where the same products are sold cyclically.

STEP 3: Demand forecasting by machine learning is performed using the features obtained in STEPs 1 and 2.

The details of each step are explained in Section IV.

A. Problem Setting

Generally, bento menu items sold by bento delivery service companies have the following characteristics.

Characteristic 1: Two types of bento menus are available: one that sells the same products periodically and another that sells different products every day.

Characteristic 2: Because the combination of products on the bento menu changes daily, demand fluctuates considerably depending on the popularity of the products on the bento menu.

Characteristic 3: The demand for bento menu items fluctuates depending on external factors such as temperature and weather conditions.

These characteristics were used to quantify the popularity of products on the bento menu.

To illustrate characteristics 1 to 3, an example of sales volume and demand variation for each bento is shown in Table I and Fig. 1. In this study, the term "bento menu item" refers to categories such as daily bento and bowl bento (Table I). The term "bento menu product" refers to the individual products that constitute the bento menu, such as Fried chicken and Ham steak (Table I). Based on characteristic 1, bento menus can be categorized into two types. The first type is the Daily Bento in Table I, in which a different product is sold daily. The second type is a bento menu that cyclically sells the same product, such as Bowl Bento, as shown in Table I. Regarding characteristic 2, as

TABLE I
Example of Bento Sold and Sales Volume

Sales Date	Temp. (°C)	Daily Bento (Sales volume)	Bowl Bento (Sales volume)	...	Noodle Bento (Sales volume)
6/15	25.3	Fried chicken (2500)	Tempura bowl (500)	...	Wild vegetables soba (400)
6/16	26.5	Ham steak (2680)	Curry rice (350)	...	Kitsune udon (420)
⋮	⋮	⋮	⋮	...	⋮
6/29	28.2	Fish (2390)	Tempura bowl (590)	...	Wild vegetables soba (480)
⋮	⋮	⋮	⋮	...	⋮

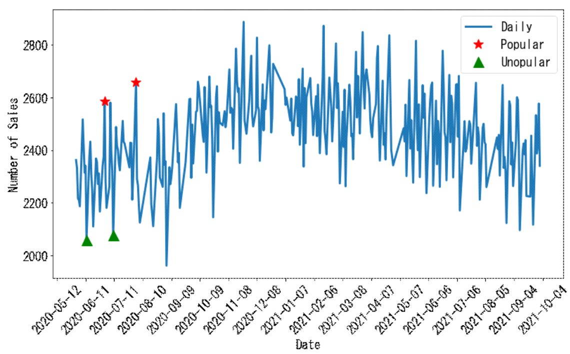

Fig. 1. Examples of demand fluctuations due to product popularity

shown in Fig. 1, demand fluctuates considerably depending on the product's popularity. If a bento menu product is popular, its sales volume tends to be higher than the average sales volume of the menu. On the other hand, if a bento menu product is unpopular, its sales volume tends to be lower than the average sales volume of the bento menu. Regarding characteristic 3, bento menus are offered with sales increasing or decreasing depending on the temperature such as Noodle Bento in Table I.

B. Quantifying Product Popularity Based on Rating Systems

In this study, we constructed a Bayesian statistical model based on rating systems to estimate the popularity of bento menu products. The model parameters were estimated using Markov chain Monte Carlo (MCMC) sampling [10]. The sales volume of bento menu products is considered to match that of sports or video games. Win-loss data were generated by comparing sales volumes. Hence, we considered that the product popularity of a bento menu was analogous to the strength of an athlete at a sporting event.

1) Research on Rating Systems: Several rating methods have been developed to evaluate team and player performance. Examples include ELO and Glicko ratings. Many recent studies have treated player and team strengths as random variables. Several methods based on Bayesian statistics have been proposed. Herbrich et al. [11] developed "TrueSkill", a graphical model-based rating system. Peiris et al. [12] extended the ELO rating with a Bayesian statistical model. Furthermore, MCMC sampling [10] was applied to estimate model parameters.

In this study, based on characteristic 2 presented in Section III-A, we related the comparison of the sales volume of bento menu products to a match in sports or video games. A match winner was the product with the highest sales volume. The product with the lowest sales volume is the loser of the match. In this case, the winner's product is considered more popular than the loser's product.

2) Difficulty in Generating Win-Loss Data: Bento delivery service companies generally offer multiple competing variations of bento menus. Menus typically feature different products and combinations of products.

Creating win-loss data that extracts only the effect of product popularity is challenging. For example, we compare the sales volumes of Tempura bowl on 6/15 and Curry rice on 6/16 in Table I. In this case, we consider Tempura bowl more popular than Curry rice because it has a larger sales volume. However, it should be noted that Tempura bowl may be less popular than Curry rice. In this case, the sales volume of Tempura bowls and Wild vegetable soba may have increased because Fried chicken was unpopular. The sales of a few bento menus such as Noodle Bento increase or decrease depending on the temperature.

Based on characteristics 1, 2, and 3 presented in Section III-A, we considered the influence of the popularity of other bento menu products and external factors such as temperature and season. When comparing (match) the sales volume of bento menu products on two randomly selected sales dates, the bento menu products that cyclically offer the same products may differ from each other. The outcome of a match can be influenced by the popularity of the bento menu sold simultaneously. If the two sales dates are far apart, the match outcome may be affected by temperature and season.

IV. Details of The Proposed Algorithm

A. Notation

In this study, we propose a demand forecasting algorithm that considers the popularity of products. We consider that product popularity affects sales volume ratio. The notations used in the proposed algorithm are as follows:

- K: Number of bento menu items sold.
- $B = \{b_0, b_1, \cdots, b_{K-1}\}$: Set of bento menu items sold.
- λ: Cycle of sales of products on bento menus where the same products are sold cyclically.
- b_0: Bento menu with different products sold every day.
- $H = \{b_1, b_2, \cdots, b_{K-1}\}$: A set of bento menus selling the same product in cycle λ.
- N: Number of sales dates.
- $D = \{1, 2, \cdots, N\}$: Set of sales dates.
- I_0: Number of products in the bento menu b_0.
- $M_0 = \{1, 2, \cdots, I_0\}$:Set of product numbers for the bento menu b_0.
- I_h: Number of products in the bento menu $h \in H$.
- $M_h = \{1, 2, \cdots, I_h\}$: Set of product numbers for bento menu $h \in H$.
- J_d^h: Set of sales dates for comparison of sales date d to sales volume ratio for the bento menu $h \in H$.
- $G_h = \sum_{d \in D} |J_d^h|$: Number of bento menu $h \in H$ match.
- $T_h = \{1, 2, \cdots G_h\}$: Set of match numbers for bento menu $h \in H$.
- θ_c: Threshold for considering two sales dates to be close.
- θ_s: Threshold for deeming two products in bento menu b_0 to be the same product.
- $X_{0,d}$: Sales volume of the bento menu b_0 on sales date $d \in D$.
- $X_{h,d}$: Sales volume of bento menu $h \in H$ on sales date $d \in D$.
- $Y_{0,d}$: Product $m_0 \in M_0$ sold on sales date $d \in D$ of the bento menu b_0
- $Y_{h,d}$: Product $m_h \in M_h$ sold on sales date $d \in D$ of bento menu $h \in H$

The details of STEP 1 are provided in Section IV-B. The details of STEP 2 are described in Section IV-C. STEP 3 is explained in Section IV-D.

B. Algorithm for Quantifying Product Popularity of Bento Menu b_0

In STEP 1, the popularity of the product is estimated for the bento menu b_0, in which a different product is sold daily. A comparison (match) of the sales volume ratio was performed for the sales dates d and $d+\lambda$. With characteristics 1 and 3 described in Section III-A, we removed the effects of the popularity of the products in the bento menu $h \in H$ and of external factors such as temperature and season.

The detailed procedure for STEP 1 of the demand forecasting algorithm is as follows: Because STEP 1 is practically the same as in the previous model [6], we omitted a few explanations.

STEP 1-1: From $X_{0,d}$ and $X_{h,d}$, the sales ratio $R_{0,d}$ is calculated.

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STEP 1-2: The match win-loss data $W[t_0]$ and $L[t_0]$ are generated by comparing the sales volume ratios $R_{0,d}$ and $R_{0,d+\lambda}$ of bento b_0 on sales dates d and $d+\lambda$, respectively.

STEP 1-3: From the win-loss data, the popularity $\mu^0[m_0]$ of product m_0 was estimated with MCMC sampling [10].

C. Algorithm for Quantifying Product Popularity of Bento Menu $h \in H$

In STEP 2, we estimate the product popularity of the bento menu $h \in H$, in which the same product is sold cyclically. A comparison of the sales volume ratio was performed for the sales dates $d \in D$ and $j \in J^h_d$. The influence of the product of bento menu b_0 was removed using the results of the product popularity of bento menu b_0 estimated in STEP 1. The effects of the temperature and season were removed through characteristic 3 in Section III-A.

The detailed procedure for STEP 2 of the demand forecasting algorithm is as follows:

STEP 2-1: From $X_{0,d}$ and $X_{h,d}$, sales ratio $R_{h,d}$ is calculated using Equation (1).

$$R_{h,d} = \frac{X_{h,d}}{X_{h,d} + X_{0,d}}, \quad d \in D. \tag{1}$$

STEP 2-2: Extract the sales dates $j \in J^h_d$ that satisfy Equations (2) and (3).

$$v - d \leq \theta_c,\ v > d,\ d, v \in D, \tag{2}$$
$$|\mu^0[Y_{0,d}] - \mu^0[Y_{0,v}]| \leq \theta_s,\ v > d,\ d, v \in D, \tag{3}$$

where θ_c is the threshold value judging whether the sale dates d and v are close or not. Additionally, θ_s is the threshold to judge whether the products $Y_{0,d}$ and $Y_{0,v}$ in bento b_0 are the same product or not (Details are provided in Algorithm 1).

STEP 2-3: The match $W[t_h]$ and $L[t_h]$ are generated by comparing the sales volume ratios $R_{h,d}$ and $R_{h,j}$ of bento $h \in H$ on the sales dates $d \in D$ and $j \in J^h_d$, respectively (Details are provided in Algorithm 2).

STEP 2-4: From the win-loss data, the popularity $\mu^h[m_h]$ of product m_h was estimated by MCMC sampling [10] using Equations (4) - (8) as

$$P[t_h, 1] \sim \mathcal{N}(\mu^h[W[t_h]], \sigma[W[t_h]]^2),\ t_h \in T_h, \tag{4}$$
$$P[t_h, 2] \sim \mathcal{N}(\mu^h[L[t_h]], \sigma[L[t_h]]^2),\ t_h \in T_h, \tag{5}$$
$$P[t_h, 1] > P[t_h, 2], \quad t_h \in T_h, \tag{6}$$
$$\mu^h[m_h] \sim \mathcal{N}(0, \sigma_\mu^2), \quad m_h \in M_h, \tag{7}$$
$$\sigma[m_h] \sim Gamma(\alpha, \beta), \quad m_h \in M_h, \tag{8}$$

where $P[t_h, 1]$ and $P[t_h, 2]$ denote the strengths of the winning (higher sales ratio) and losing (lower sales ratio) products in the t_h-th match (comparison of the sales volume ratio), respectively. $\mu^h[m_h]$ and $\sigma[m_h]$ are the mean and variance of the strength of product m_h, respectively. $W[t_h]$ and $L[t_h]$ are products m_h of the winners and losers in match number t_h for the bento menu $h \in H$, respectively. $\mathcal{N}(a, b^2)$ denotes a normal distribution with mean a and variance b^2. Equations (4) and (5) show that $P[t_h, 1]$ and $P[t_h, 2]$ follow normal distributions. Equation (6) indicates that the winners' performance is better than that of the losers. Equation (7) states that the popularity of product m_h follows a normal distribution with mean 0 and variance σ_μ^2. Equation (8) shows that the variance of the popularity of product m_h follows a gamma distribution with α and β as parameters.

The details of STEPs 2-2 and 2-3 are shown in Algorithms 1 and 2.

Algorithm 1 Extraction of sales date $j \in J^h_d$ (STEP 2-2)

Input: N, $Y_0[d](= Y_{0,d})$, $\mu^0[m_0]$, θ_c, θ_s
Output: $J^h[d](= J^h_d)$

```
for d ← 1, N do
    J^h[d] = set( )
    for c ← 1, θ_c do
        v = d + c
        if v ≤ N and |μ^0[Y_0[d]] − μ^0[Y_0[v]]| ≤ θ_s then
            J^h[d].add(v)
        end if
    end for
end for
```

Algorithm 2 Creation of win-loss data (STEP 2-3)

Input: N, $J^h[d](= J^h_d)$, $R_h[d](= R_{0,d})$, $Y_h[d](= Y_{h,d})$
Output: $W[t_h]$, $L[t_h]$

```
t_h = 0
for d ← 1, N do
    for all j ∈ J^h[d] do
        t_h = t_h + 1
        if R_h[d] > R_h[j] then
            W[t_h] = Y_h[d]
            L[t_h] = Y_h[j]
        else
            W[t_h] = Y_h[j]
            L[t_h] = Y_h[d]
        end if
    end for
end for
```

The product popularity of the bento menu $h \in H$ is estimated by comparing the sales volume ratio of the product on sales dates $d \in D$ and $j \in J^h_d$. To estimate the product popularity of bento menu $h \in H$, the influence of the product popularity of bento menu b_0 should be considered. We compared the sales volume ratios of the bento menu $h \in H$ on the sale dates on which the popularity of the products on bento menu b_0 was approximately the same. We removed the effect of the product popularity of the bento menu b_0 by hypothetically assuming that it sold the same product. Additionally, external factors such as temperature and season should be considered. To eliminate these effects, we compared the sales volume ratios of the products on sales dates $d \in D$ and $j \in J^h_d$ extracted by Algorithm 1.

D. Features Used in Machine Learning for Demand Forecasting

We used machine learning to forecast the demand for bento menu items based on the features calculated in STEPs 1

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and 2, which estimated product popularity. The features were classified into four types: (1) the estimated total sales volume of products for the forecast date, (2) product popularity of each bento sold on the forecast date, (3) sales volume of each bento for several cycles, and (4) product popularity of each bento for several cycles. The second and fourth feature types are obtained using STEPs 1 and 2, respectively.

This study examined gradient boosting and RF as demand-forecasting models. LightGBM (LGBM) was used for gradient boosting. Neural networks, which are widely used to forecast time series data, generally struggle to handle missing values. A neural network is considered inappropriate for this study because bento sales data generally contain missing values.

V. Numerical Experiment

We validated the efficacy of the proposed algorithm by analyzing real-world sales data obtained from a Kanagawa Prefecture company that produces and delivers 13,000 bento per day. The company sells three types ($K = 3$) of bento menu. The company sells daily bento (b_0), which is not cyclical in sales. The company offers bowl and noodle bento menus (b_1, b_2) that sell the same products in a λ cycle. Additionally, noodle bento is switched between cold and hot depending on the season. In this study, we forecast the period during which noodle bento menus were sold as cold noodle products. Interviews with the company's forecasters revealed that it could replenish its inventory within a certain range. The replenishment quantity was approximately 3% of the production volume.

The programming language used for the implementation was Python 3.9.7, and the operating environment was CPU: Ryzen5 5950x, RAM: 128GB, and OS: Windows 11. For the machine-learning programs, we used Python LightGBM ver. 3.2.1 and Scikit-learn ver. 0.24.2. For the popularity estimation programs, we used the Python library Pystan ver. 2.19.1.1.

A. Results of Product Popularity Estimation for Bento Menus

This section presents the results of the popularity estimation method described in Section IV-C. The data used to estimate the product popularity of bento was the number of sales dates, $N = 358$. The parameters were $\lambda = 10$, $\theta_c = 15$, $\theta_s = 1$, $\alpha = 150$, and $\beta = 10$. The number of bowl bento (b_1) products was set to $I_1 = 12$.

Approximately 80% of the customers of the company that provided data were factory workers. Interviews with this company revealed that meat products are more popular than vegetables or fish products. Deep-fried products are popular.

Table II shows a few of the results of the estimated μ of the product popularity of bowl bento's product popularity. The results presented in Table II are consistent with the company's findings. The first-ranked product was a fried meat dish. A large difference is observed between the third and fourth place values of μ. Products ranked fourth or lower may have not interested customers, or may not have been an option for customers. Customers may have shunned these products because they could not imagine what kind of food these products would be. Customers may have lost interest in the fourth-place Chicken and egg rice bowl. Companies in the delivery bento industry, which are sensitive to boredom, regularly improve their products. However, interviews with the company revealed that Chicken and egg rice bowl could not be improved. Beef rice bowl and Curry rice are less popular because many restaurant chains in Japan serve beef and Curry rice. They may not be options for customers because they are readily available at any time.

TABLE II
Popular and unpopular products for rice bowl bento

Rank	Products	Estimated value(μ)	Rank	Products	Estimated value(μ)
1	Deep-fried pork cutlet rice bowl	11.1	8	Korean BBQ rice bowl	-0.1
2	Tempura rice bowl	6.8	9	Curry rice	-1.4
3	Salted pork rice bowl	5.8	10	Stamina rice bowl	-1.9
4	Chicken and egg rice bowl	1.0	11	Gapao rice	-2.1
5	Chinese style starchy sauce rice bowl	0.8	12	Beef rice bowl	-2.3

B. Accuracy Comparison of Demand Forecast Models

This section presents the results of the demand forecasting model described in Section IV-D. We compared the prediction accuracy of several machine-learning algorithms, a previous model [6], and forecasters. The hyperparameter settings for the machine-learning algorithms used in this study were library defaults. The processing times for LGBM and RF were 9.2 and 51.7 s, respectively.

We examined prediction accuracy over two time frames: full-time and immediately following a forecaster switch. This company replaced its demand forecaster in March 2020. The prediction accuracy was not compared with that of the previous forecaster, because no prediction values were available for the previous forecaster. The forecast period for the entire period was from April 6, 2020 to October 31, 2021. The period immediately following the change in the forecaster is defined as the period between April 6, 2020 and October 31, 2020. In both cases, the learning period was until the previous date of the forecast. The period from April 1, 2020 to July 12, 2020 was excluded from the comparison because of the impact of the COVID-19 pandemic. We have reported some of our forecasts from March 2020 on to the company that provides the data.

1) Evaluation index of the demand forecast model: Two types of indicators were developed to assess the usefulness of the model. The first type is the mean percentage error (MPE^+) and its standard deviation (SD^+) when the predictions are higher than the actual values. The second type is the mean percentage error (MPE^-) and its standard deviation (SD^-) when the predictions are lower than the actual values. MPE^+, SD^+, MPE^-, and SD^- are defined as follows:

$$MPE^+ = \frac{1}{N} \sum_{d \in D} \epsilon_d^+, \tag{9}$$

$$SD^+ = \sqrt{\frac{1}{N} \sum_{d \in D} (s_d^+)^2}, \tag{10}$$

$$MPE^- = \frac{1}{N} \sum_{d \in D} \epsilon_d^-, \tag{11}$$

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$$SD^- = \sqrt{\frac{1}{N}\sum_{d\in D}(s_d^-)^2}, \tag{12}$$

where ϵ_d^+, s_d^+, ϵ_d^-, and s_d^- are defined from the Equations (13), (14), (15), and (16), respectively.

$$\epsilon_d^+ = \begin{cases} 0 & (f_d - x_d < 0) \\ \frac{f_d - x_d}{x_d} & (f_d - x_d \geq 0) \end{cases}, \quad d \in D, \tag{13}$$

$$s_d^+ = \begin{cases} 0 & (f_d - x_d < 0) \\ \epsilon_d^+ - \bar{z} & (f_d - x_d \geq 0) \end{cases}, \quad d \in D, \tag{14}$$

$$\epsilon_d^- = \begin{cases} \frac{f_d - x_d}{x_d} & (f_d - x_d < 0) \\ 0 & (f_d - x_d \geq 0) \end{cases}, \quad d \in D, \tag{15}$$

$$s_d^- = \begin{cases} \epsilon_d^- - \bar{z} & (f_d - x_d < 0) \\ 0 & (f_d - x_d \geq 0) \end{cases}, \quad d \in D, \tag{16}$$

where f_d is the forecasted value on sales date d and x_d is the observed value. $\frac{f_d - x_d}{x_d}$ is the prediction error rate. $\bar{z}$ denotes the mean prediction error rate. $\epsilon_d^+ - \bar{z}$ and $\epsilon_n^- - \bar{z}$ denote the deviation. Equations (13) and (14) are set to 0 if the prediction error is < 0 to consider cases in which the predicted value is greater than the actual value. Similarly, Equations (15) and (16) set the prediction errors to 0 when they are ≥ 0 to account for cases where predicted value is less than the actual value.

Therefore, MPE^+ represents the average percentage of food loss and SD^+ denotes the variation in MPE^+. In the bento-delivery industry, MPE^+ must be decreased to reduce food loss. MPE^- represents the average percentage deficiency and SD^- denotes the variation in MPE^-. Bento delivery companies can compensate for this shortcoming to some extent. However, if MPE^- is too large, additional production is required to cover the shortage, which burdens production.

2) Comparative Results of Prediction Accuracy: Over two time periods, we compared the prediction accuracy of different machine-learning algorithms. Table III displays the results of the comparison of the accuracy of daily bento (b_0) forecasts for the entire period. Table IV presents the results of the comparison of the accuracy of the daily bento (b_0) immediately after the change in the forecaster. Fig. 2 depicts the prediction results, with the actual value (dotted line) and prediction by the LGBM (solid line). Each indicator in Tables III and IV is indicated in bold font and has the smallest value among the LGBM, RF, and previous models. The evaluation indices are the values calculated using Equations (9) - (12) and the mean absolute percentage error ($MAPE$).

TABLE III
COMPARISON OF PREDICTION ACCURACY OF DAILY BENTO OVER THE FULL PERIOD

	LGBM	RF	Previous model [6]	Field forecaster
MPE^+ (%)	1.64	1.96	**1.63**	1.69
SD^+	1.90	1.98	**1.83**	2.44
MPE^- (%)	1.88	**1.60**	1.93	1.55
SD^-	3.72	**3.51**	3.55	3.09
$MAPE$ (%)	**3.52**	3.56	3.56	3.25

Table III shows that the LGBM has the best balance of all indicators compared to the prediction accuracy of the RF and previous models [6]. Additionally, we observed that LGBM had the lowest $MAPE$. MPE^- in LGBM was smaller than in the previous model. MPE^+ of the LGBM is only slightly larger than that of the previous model. Additionally, when MPE^- of LGBM and RF is $\leq 3\%$, the shortfall can be replenished.

TABLE IV
PREDICTIONS BY FORECASTER AND MACHINE LEARNING ON DAILY BENTO (IMMEDIATELY AFTER CHANGE OF FORECASTER)

	LGBM	RF	Previous model [6]	Field forecaster
MPE^+ (%)	**1.61**	1.98	1.62	1.71
SD^+	1.77	2.05	**1.70**	3.10
MPE^- (%)	1.98	**1.53**	2.01	2.12
SD^-	4.47	**3.92**	4.18	3.30
$MAPE$ (%)	3.59	**3.52**	3.63	3.83

Table III shows that the LGBM and RF are as accurate as the forecaster's predictions. For MPE^+, the LGBM was superior to the forecaster prediction. When comparing MPE^- results, no significant difference was observed between RF and forecaster predictions. For SD^+, which indicates the variation in the predictions, LGBM and RF obtained lower values than the person in the forecaster's predictions. The prediction accuracy of the proposed algorithm needs to be improved because the best $MAPE$ value was predicted by the forecaster.

If the person in charge is not familiar with forecasting operations, machine-learning forecasts may reduce food and opportunity losses. Table IV shows that the RF has the best balance of all indicators compared to the prediction accuracy of the LGBM and previous models [6]. Additionally, we observed that RF had the lowest $MAPE$. The forecasting accuracy of LGBM was superior to that of the forecaster.

Machine-learning forecasting can assist forecasters and improve their prediction ability. When comparing the accuracy of the forecaster's predictions for the entire period (Table III) with those immediately after the switch (Table IV), the forecaster's accuracy was higher for the entire period. Interviews with forecasters revealed that they regularly consult weekly forecast values.

The designed features were obtained to be highly accurate and independent of machine-learning algorithms. As shown in Tables III and IV, no significant differences are observed between the LGBM and RF evaluation indices. Additionally, RF and LGBM performed as well as or better than the previous model [6]. The previous model [6] only considered the product popularity of a single bento menu item. We confirmed the usefulness of considering the product popularity of multiple bento menu items.

VI. CONCLUSIONS

We propose a method for estimating the product popularity of multiple types of bento menu items using Bayesian statistics based on a rating system. We developed a machine-learning model for demand forecasting that considers the estimated popularity of a product. Furthermore, we conducted a numerical experiment using actual sales data from a bento delivery service company. Numerical results indicated that the proposed algorithm outperformed previous methods [6]. No significant difference was observed in prediction accuracy between RF and LGBM. A comparison with a previous model [6] demonstrates the usefulness of considering the popularity of multiple types of bento menus. A few indicators

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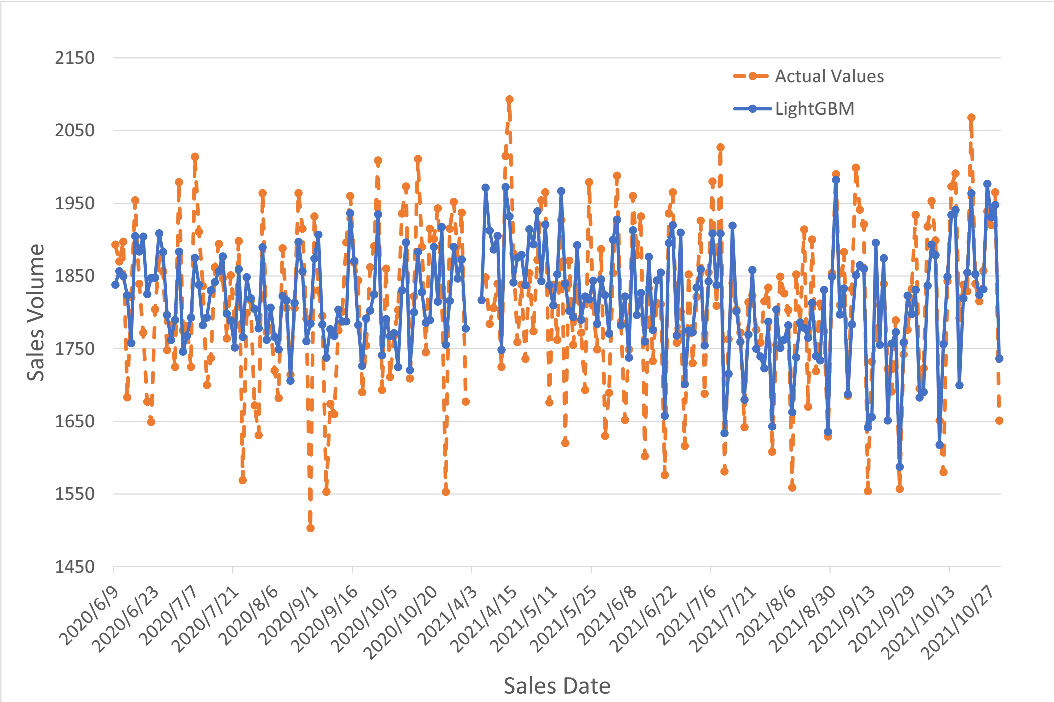

Fig. 2. Predicted results for daily bento over the full period

have better values than those predicted by company's forecasters. The proposed algorithm can help forecasters improve their skills.

Several additional approaches can be implemented for further improving the prediction accuracy of the proposed algorithm. The first idea is to consider temperature effects. There are some types of bento menu items for which the demand varies with changes in temperature. Further analysis is required because the effects of temperature vary depending on the season. The second idea is to adjust the estimated popularity value of the product. The forecasted values for extremely popular and unpopular products tend to differ significantly from the actual sales volumes. Adjusting the estimated popularity values may improve prediction accuracy.

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References

[1] "Ministry of internal affairs and communications, statistics bureau," https://www.stat.go.jp/data/kkj_2020/kekka/index.html, [accessed Dec. 2022].

[2] "Ministry of the environment, government of japan: Food loss and recycling (2022)," https://www.maff.go.jp/j/shokusan/recycle/syoku_loss/attach/pdf/161227_4-52.pdf, [accessed Nov. 2022].

[3] N. S. Arunraj, D. Ahrens, and M. Fernandes, "Application of sarimax model to forecast daily sales in food retail industry," *International Journal of Operations Research and Information Systems*, vol. 7, no. 2, pp. 1–21, 2016.

[4] S. Punia, K. Nikolopoulos, S. P. Singh, J. K. Madaan, and K. Litsiou, "Deep learning with long short-term memory networks and random forests for demand forecasting in multi-channel retail," *International journal of production research*, vol. 58, no. 16, pp. 4964–4979, 2020.

[5] X.Dairu and Z. Shilong, "Machine learning model for sales forecasting by using xgboost," in *2021 IEEE International Conference on Consumer Electronics and Computer Engineering*, 2021, pp. 480–483.

[6] K. Ota and H. Katagiri, "Demand forecasting of bento considering the product popularity estimation by bayesian rating system," *International Journal of Japan Association for Management Systems*, Submitted.

[7] L. Woltmann, J. Drechsel, C. Hartmann, and W. Lehner, "Ingredient-based forecast of sold dish portions in campus canteen kitchens," in *2022 IEEE 38th International Conference on Data Engineering Workshops (ICDEW)*, 2022, pp. 111–116.

[8] T. Trzciński and P. Rokita, "Predicting popularity of online videos using support vector regression," *IEEE Transactions on Multimedia*, vol. 19, no. 11, pp. 2561–2570, 2017.

[9] S. Mehrizi, A. Tsakmalis, S. Chatzinotas, and B. Ottersten, "A bayesian poisson-gaussian process model for popularity learning in edge-caching networks," *IEEE Access*, vol. 7, pp. 92 341–92 354, 2019.

[10] D. Van Ravenzwaaij, P. Cassey, and S. D. Brown, "A simple introduction to markov chain monte–carlo sampling," *Psychonomic bulletin & review*, vol. 25, no. 1, pp. 143–154, 2018.

[11] R. Herbrich, T. Minka, and T. Graepel, "Trueskill: a bayesian skill rating system," *Advances in neural information processing systems*, vol. 19, 2006.

[12] T. S. N. Peiris and R. M. Silva, "Player ranking in taekwondo: A bayesian elo rating system," in *2020 From Innovation to Impact (FITI)*, vol. 1, 2020, pp. 1–5.