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Food Recommendations to Support Unsold Food Marketplace Using Content-Based Filtering

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***Abstract*—Unsold food is food that has a short shelf life, is intended to be sold, and is still edible. Based on survey results, business owners usually resell unsold food at a discounted price via WhatsApp or posters placed in front of the shop or distribute it to the surrounding community. Meanwhile, consumers buy unsold food by visiting the shop directly. Unsold food promotions via WhatsApp or posters do not reach the wider community. Meanwhile, direct purchases limit the opportunity to buy unsold food from several sellers simultaneously and increase the risk of stockouts, which can lead to wasted food and missed savings for consumers. This study aims to develop an unsold food marketplace integrated with two key features: bargaining and recommendations. Recommendations are generated using content-based filtering with cosine similarity to measure the similarity between the user's purchase history and each unsold food item. The recommendation feature's findings reveal that content-based filtering generates recommendations more in line with user preferences than popularity-based ones. Validation results confirm this finding, demonstrating 100% accuracy in matching the recommended food categories with the ones users have purchased. Meanwhile, during the marketplace validation stage, 15 respondents reported strong acceptance, with average scores of 4.67 out of 5 for usefulness and 4.71 out of 5 for usability. This study highlights how an unsold food marketplace supports consumers with limited budgets, reduces food waste, and increases seller revenue, while its bargaining and recommendation features enhance user satisfaction and engagement, thereby achieving mutual benefits.**

***Index Terms*—Content-based filtering, cosine similarity, food waste, marketplace, recommendation, unsold food.**

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I. Introduction

The development of food and beverage businesses in Indonesia showed a significant increase in 2023 [1]. In the year, there were 4.85 million food and beverage businesses. This number represents an increase of 20.98% compared to 2019. Several factors contributed to this significant increase, including changes in people's lifestyles, especially among those living in urban areas, and the development of the internet. The growing busyness of urban communities has driven up fast-food consumption. In addition, the development of the internet has enabled the growth of delivery service applications [2]–[4] and the promotion of products via social media and other online platforms. The ease of ordering food and drinks through applications, the availability of sales promotions such as discounts, positive customer reviews, attractive food visuals, and the influence of influencers also contribute to increased fast food consumption. The aforementioned conditions offer significant potential for food and beverage business owners in Indonesia to continue growing.

The large number of food and beverage businesses, short sales periods, and unpredictable consumer demand can lead to excess unsold food. Unsold food with a short shelf life but still edible is a challenge for food business operators [5]. Some strategies adopted by food business operators to address unsold food include donating it to food banks or charities [6], distributing it to employees or neighbors, reselling it with promotions, or throwing it away [7]. Food that is thrown away becomes waste, which can increase waste management costs, reduce income, and threaten food security [8]. In some countries, food waste is a significant contributor to overall waste [9], [10]. Indonesia is the country with the second-largest food waste contribution in Southeast Asia [11].

On the other hand, the percentage of households in Indonesia receiving food assistance programmes and the percentage receiving the Family Welfare Programme (WFP) increased from 2020 to 2024 [12]. WFP is a conditional cash transfer program targeted at low-income and socially vulnerable families [13]. Approximately 87.91% of recipient households utilize the WFP for grocery shopping. Therefore, efforts to resell unsold food with certain promotions can reduce food waste, increase sales revenue, and help consumers with

limited budgets.

Various studies have been conducted to address food waste and unsold food. One of them is Re-Food, a prototype of a digital platform-based business model innovation based on a food-sharing scheme [14]. The main features of Re-Food are Food Around Me, Food Hero, My Order, and My Reward. Re-Food users can buy surplus food from Re-Food partners through the food around me feature or donate it to people in need through the food hero feature. This study employed a qualitative descriptive approach and a business model innovation framework. The results showed that 97% of respondents were interested in using the Re-Food application.

RescuePlate is a prototype developed as a web-and mobile-based platform [15]. It was designed to reduce food waste in the Philippines by engaging local communities, food businesses, and non-governmental organizations focused on social initiatives. The application enables users to purchase, donate, or request surplus food. Findings from the study indicate that RescuePlate's functionality and usability received positive user feedback.

In addition, several applications have been developed to facilitate the sharing or sale of surplus food from various restaurants, cafes, and shops in various countries, either for free or at a discounted price [16]. Olio, ResQ Club, and Too Good To Go are some examples of applications that share or sell unsold food. Apart from features for sharing or selling, these applications also offer review and rating functionalities. The Olio application even includes a points feature that rewards users. Points can be earned through various activities such as sharing items and providing ratings. However, the points obtained cannot be used for any purpose. One of the core activities in business is bargaining to gain mutual benefits. This feature is not yet available in these applications, nor is the recommendation feature, which helps accelerate search results based on personalized user preferences.

Recommendation systems have been widely used to accelerate the search for relevant information [17]–[25]. Some examples of the use of recommendation systems include facilitating food search [26], [27], correcting frequently mistyped words [28], and selecting specialized options [29]. Two commonly used techniques to generate recommendations based on user preferences and behavior are Content-Based Filtering (CBF) and Collaborative Filtering (CF) [23]. Some researchers use a hybrid of CBF and CF to develop recommendations [23], [27]. However, most surplus food recommendation systems are not connected to other systems.

Most existing surplus food apps only allow users to purchase food at lower prices or receive free food donations. To find the surplus food they want, users can use the search feature. Generally, users search for surplus food that matches their preferences. The problem is that the lengthy search process can cause the desired surplus food to run out, as the quantity sold is usually limited. Furthermore, the bargaining feature, a key business activity for mutual benefit, is not yet available in existing apps. Therefore, this study aims to develop a marketplace for the sale of unsold food. The proposed marketplace will include a bargaining feature and recommendations for unsold food based on the history of purchased unsold food categories. The bargaining feature is expected to increase consumer interest in buying and boost sales volume. Meanwhile, the recommendation feature is intended to facilitate and expedite the search for preferred unsold food items. This study introduces the integration of bargaining and recommendation features in an unsold food marketplace to enhance user engagement and satisfaction.

II. Research Method

To identify the marketplace requirements, semi-structured interviews were conducted with four food business owners in East Java, Indonesia. The four business premises were randomly selected, and the participants were willing to participate in this study. In addition, questionnaires were distributed to the public to identify the marketplace requirements from the buyer's perspective. The questionnaires were distributed using a simple random sampling technique.

One of the key features of the developed marketplace is a personalized system for recommending unsold food. The method used to generate these recommendations is content-based filtering with cosine similarity. Recommendations are generated based on the history of unsold food categories purchased and the unsold food currently offered by the seller. The steps taken in generating the recommended unsold food are depicted in Fig. 1.

The recommendation process begins by constructing a vector called the Purchase History Vector (PHV). The PHV consists of n elements, where n represents the number of recorded unsold food categories. Each element of the PHV represents the number of items of unsold food ever purchased in the related category.

Next, an unsoldFood vector is constructed for each unsold food item available at that time. Each unsoldFood vector consists of n elements. The i-th element of the unsoldFood vector is assigned a value of 1 if the unsold food item belongs to the corresponding category and 0 if it does not.

Once both types of vectors are constructed, the similarity between the PHV and each unsoldFood vector is calculated. The similarity between two vectors is calculated using (1). Equation (2) is used to calculate the dot product of two vectors of length n, while (3) is used to calculate the norm of a vector.

$$\text{Cosine Similarity } (\vec{x}, \vec{y}) = \frac{\vec{x} \,.\, \vec{y}}{\|\vec{x}\| \, \|\vec{y}\|} \tag{1}$$

$$\vec{x} \,.\, \vec{y} = \sum_{i=1}^{n} x_i * y_i \tag{2}$$

$$\|\vec{x}\| = \sqrt[2]{\sum_{i=1}^{n} x_i^2} \tag{3}$$

where $\vec{x}$ and $\vec{y}$ each represent a vector, $\|\vec{x}\|$ is the magnitude of vector $\vec{x}$, and $\|\vec{y}\|$ is the magnitude of vector $\vec{y}$.

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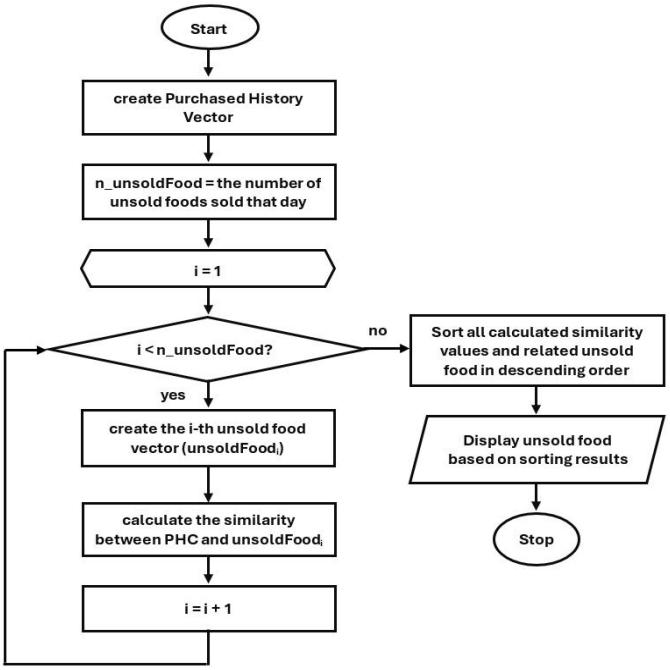

Fig. 1. Recommendation process flowchart.

Finally, all cosine similarity values are sorted in descending order, and the available unsold food items are displayed based on their recommendation ranking. The most recommended unsold food item is the one with the highest cosine similarity score; conversely, the least recommended is the one with the lowest.

To illustrate how the recommendation process works, a list of unsold food items and a buyer's purchase history, as shown in Table 1, are used. According to Table 1, the value of n, the number of food categories sold, is three. The PHV vector is [3, 0, 3], where the first element represents the number of main courses ever purchased, the second represents the number of side dishes ever purchased, and the third represents the number of snacks ever purchased. Meanwhile, the unsoldFood vector is [[1, 0, 0], [1, 1, 0], [0, 0, 1], [0, 0, 1]]. The rows of the unsoldFood vector represent unsold food items, and the columns represent unsold food categories. The first element of the unsoldFood vector, [1, 0, 0], indicates that Nasi Goreng Jawa is in the main course category, but not in the side dish or snack categories.

Table 1.
Unsold Food Sold and A Person's Purchase History

Unsold Food	Categories	Quantity Purchased
Nasi goreng Jawa	Main course	3
Terong balado	Main course, side dishes	0
Wajik	Snack	2
Gabin Ragout	Snack	1

The similarity calculation between the PHV vector and the first element of the unsoldFood vector is shown in (4). Equations (5) to (7) show the similarity calculations between the PHV vector and the second to fourth elements of the unsoldFood vector. The four similarity values are then sorted in descending order. Therefore, the order of the unsold food items, from most recommended to least, is nasi goreng jawa, wajik, gabin ragout, and finally, terong balado.

$$\frac{3*1+0*0+3*0}{\sqrt{3^2+0^2+3^2}*\sqrt{1^2+0^2+0^2}} = \frac{3}{3\sqrt{2}} = 0.707 \quad (4)$$

$$\frac{3*1+0*1+3*0}{\sqrt{3^2+0^2+3^2}*\sqrt{1^2+1^2+0^2}} = \frac{3}{6} = 0.5 \quad (5)$$

$$\frac{3*0+0*0+3*1}{\sqrt{3^2+0^2+3^2}*\sqrt{0^2+0^2+1^2}} = \frac{3}{3\sqrt{2}} = 0.707 \quad (6)$$

$$\frac{3*0+0*0+3*1}{\sqrt{3^2+0^2+3^2}*\sqrt{0+0^2+1}} = \frac{3}{3\sqrt{2}} = 0.707 \quad (7)$$

The performance of the marketplace will be evaluated by verifying each marketplace feature and validating it with both seller and buyer respondents. The recommendation feature will be verified through simulations based on specific scenarios, while the other features will be verified through black-box testing [30]. The simulation data are synthetic, generated to reflect respondents' purchasing histories and preferences, enabling a realistic evaluation of the system's performance.

The simulation of the recommendation process was conducted using eight categories of unsold food with the sales history of each category as shown in Table 2, twelve kinds of unsold food items currently on sale as shown in Table 3, the purchasing history of prospective buyer A as presented in Table 4, and the purchasing history of prospective buyer B as presented in Table 5. Table 3 shows that an unsold food item can be classified into one or more categories. For example, nasi goreng Jawa is classified as both a main course and a rice dish. Based on Table 4, prospective buyer A purchased four kinds of surplus food, mostly in the main course category. Meanwhile, Table 5 indicates that prospective buyer B purchased more surplus food than buyer A. The majority of surplus food purchased by B was in the bread and cake category.

Black-box testing was carried out by providing various possible inputs, then evaluating the displayed output and/or examining the contents of the related database table. If an error occurs, corrective actions are taken immediately, followed by retesting. This process is repeated until no further errors occur.

Validation was conducted to evaluate the performance of the recommendation feature, the usefulness and usability of the developed marketplace features, and to obtain feedback for improvement. The performance of the recommendation feature was evaluated by asking three respondents to specify the categories of surplus food they would like to purchase, then running the recommendation feature after several transactions.

Table 2.
Unsold Food Category

Unsold Food Category	Quantity Sold
Main course	14
Snack	7
Desserts	20
Rice	8
Noodles	4
Side Dishes	2
Bread & Cake	11
Salad	20

Table 3.
List of Unsold Food Items for Sale

Unsold Food	Categories
Nasi goreng Jawa	Main Course, Rice
Mie goreng	Main Course, Noodles
Terong balado	Main Course, Side Dishes
Wajik, Kue tok, Gabin Ragout	Snack, Bread & Cake
Bakpao Jasio, Bakpao Tausa, Dadar gulung, Klepon	Bread & Cake
Fruit Salad	Salad
Fruit Pudding	Desserts

Table 4.
Purchase History of Prospective Buyer A

Unsold Food Purchased	Categories	Quantity Purchased
Nasi goreng Jawa	Main Course, Rice	2
Terong balado	Main Course, Side Dishes	1
Mie goreng	Main Course, Noodles	1
Gabin Ragout	Snack, Bread & Cake	1

Table 5.
Purchase History of Prospective Buyer B

Unsold Food Purchased	Categories	Quantity Purchased
Ayam bawang	Main Course, Side Dishes	1
Nasi goreng Jawa	Main Course, Rice	2
Mie goreng	Main Course, Noodles	1
Bakpao Tausa	Bread & Cake	1
Bakpao Jasio	Bread & Cake	1
Kue tok	Snack, Bread & Cake	1
Gabin Ragout	Snack, Bread & Cake	1

The recommendation system was run using the same data on surplus food items and their categories as in the verification process, along with purchase histories and preferences obtained directly from the respondents. The resulting recommendations were compared with the respondents' selected categories to assess their alignment with their stated preferences. Meanwhile, a separate validation was conducted with four food business owners in East Java and 15 buyers. First, respondents were asked to watch a demo video and then try the system. After that, semi-structured interviews were conducted with the business owners, and the other respondents were asked to fill out a questionnaire. All respondents participating in the validation process were randomly selected.

III. Result and Discussion

Based on interviews with four business owners, three stated that unsold food is still sold individually via WhatsApp or by posting posters in front of the shop, which limits outreach to potential buyers. Meanwhile, the remaining respondent currently provides only unsold food to the surrounding community for free. However, this respondent is willing to resell unsold food in the future to increase income.

The distributed questionnaire collected responses from 34 respondents, 79.4% of whom had purchased surplus food. Approximately 85.2% of respondents who had purchased surplus food reported doing so by visiting the sales location directly, while 14.8% asked friends or family to buy it. Common problems experienced by respondents include a lack of information about where surplus food is sold and arriving to find that the desired items are no longer available or have sold out.

Based on user needs, a web-based marketplace called Happy Hour was developed. Fig. 2 shows the marketplace's database design. The entities in Fig. 2 support the features provided in the marketplace system. The main features are managing unsold food sales, accepting orders, bargaining, balance withdrawals, My Points, Favorites, Ratings, and recommendations. The My Points feature is used to manage and track points earned from various activities, such as purchasing surplus food. The Favorites feature lets users manage a list of favorite sellers, while the Rating feature lets them rate and review surplus food they have purchased. Three rating aspects are available: price, flavor, and quality. When a seller is added as a favorite, users will receive a notification through their registered WhatsApp number whenever the seller opens a new surplus food sale.

The database was implemented using MySQL, and the marketplace system used Laravel 10.0 and PHP. The minimum hardware specifications required to run the marketplace system are:

- Processor: Intel Core i5
- RAM: 4GB
- Screen Resolution: 1920 x 1080.

Meanwhile, the software requirements are:

- Operating System: Windows 10/11
- Browser
- XAMPP
- Visual Studio Code
- phpMyAdmin or MySQL Workbench
- Ngrok

In addition to hardware and software, the following are also required:

- Internet connection
- A Midtrans account, integrated with the marketplace to support online payment features,
- A LocationIQ account, integrated with the marketplace to support address searches using Google Maps,
- A Twilio account, integrated with the marketplace to support sending notifications via WhatsApp.

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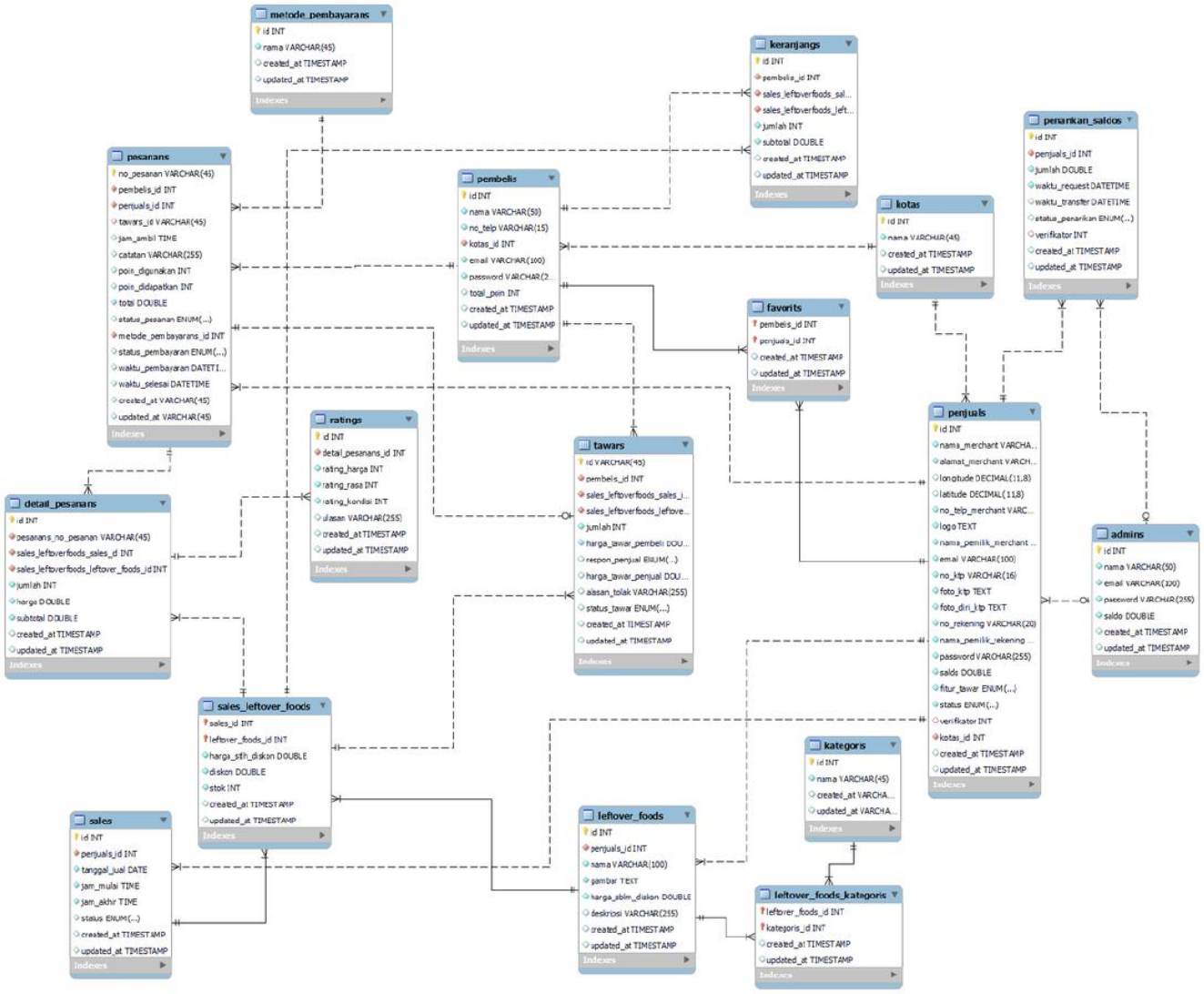

Fig. 2. Surplus food marketplace database design.

Figure 3 shows an example of the bargaining interface, one of the distinctive contributions of this research. The bargaining feature allows prospective buyers to propose prices based on the quantity they intend to purchase. Sellers can evaluate the proposed offers based on available stock, buyer interest levels, and store closing hours before deciding on an appropriate response. Sellers can accept, reject, or counteroffer the potential buyer. This bargaining process continues until an agreement is reached or one party terminates the offer. If an agreement is reached, the prospective buyer will be redirected to the checkout page. On this page, the prospective buyer can specify the pickup time, payment method, and whether to use available points. The bargaining mechanism makes negotiations more flexible and interactive, fostering engagement between buyers and sellers, and supporting the achievement of mutually beneficial outcomes.

For every 15,000 rupiah spent, buyers will receive 1 point, with multiples applying. The total points a buyer has accumulated, along with their current level, can be viewed in the My Points feature, as shown in Fig. 4. The buyer has accumulated 120 points and is currently at the Gold level. Of the 120 points collected, 100 have been used for transactions, leaving 20 points remaining. By earning an additional 320 points, the buyer can advance to the Sapphire level. The buyer can track point usage by selecting the History button or redeem the available points using the Redeem button. The My Levels feature in the Olio application, as illustrated in Fig. 5, is similar to the My Points feature. The difference between these two

features is that points in the Olio application cannot be exchanged for anything, whereas points in this study can be exchanged for surplus food. Points earned in the Olio application are used only to reward activities that have a positive impact on the community or environment [31].

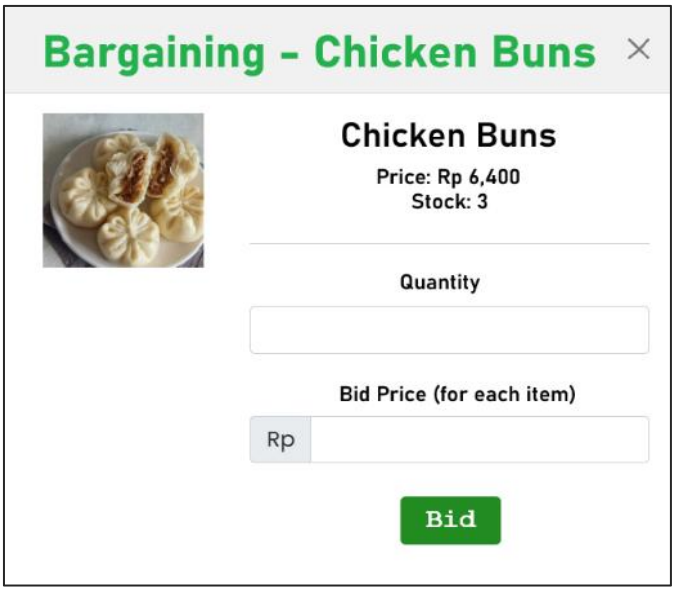

Fig. 3. Bargaining interface.

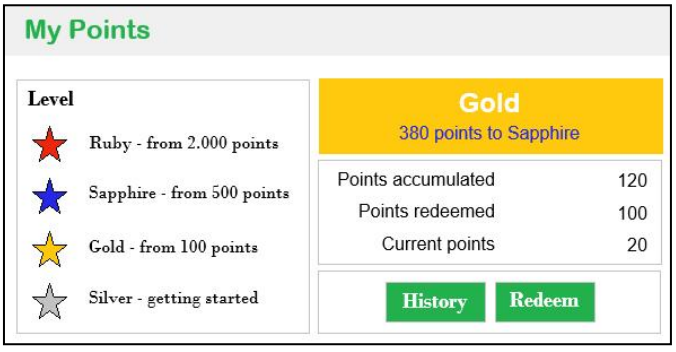

Fig. 4. My points interface.

Figure 6 presents the quantity purchased by A for each unsold food category based on Table 4. Meanwhile, Fig. 7 shows the quantity purchased by B for each unsold food category based on Table 5. The similarity between the category of unsold food that is available for sale and the history of A's purchase category is shown in Fig. 8. Meanwhile, Fig. 9 shows the similarity between the category of unsold food that is available for sale and the history of B's purchase category.

Figure 6 shows that prospective buyer A most frequently purchases the main course category and never purchases surplus food in the salad and dessert categories. Consequently, the main course category has the highest similarity score, while the salad and dessert categories have the lowest similarity scores for prospective buyer A, as shown in Fig. 8.

Figure 7 shows that prospective buyer B most frequently purchases the main course and bread and cake categories, but never purchases surplus food from the salad and dessert categories. Therefore, the main course, bread, and cake categories have the highest similarity scores, while the salad and dessert categories have the lowest for prospective buyer B, as shown in Fig. 9.

Fig. 5. My levels interface.

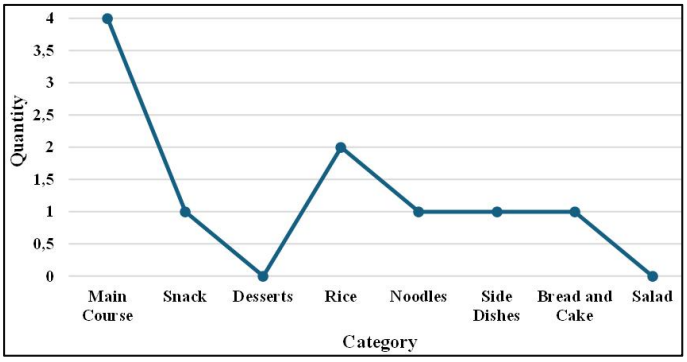

Fig. 6. Quantity purchased by prospective buyer A for each unsold food category.

The verification results of the recommendation feature for prospective buyer A are shown in Fig. 10, and those for prospective buyer B are shown in Fig. 11. In both figures, unsold food items are ranked in descending order by similarity score. Meanwhile, other feature verifications show that the output and database table updates are consistent with the given

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input.

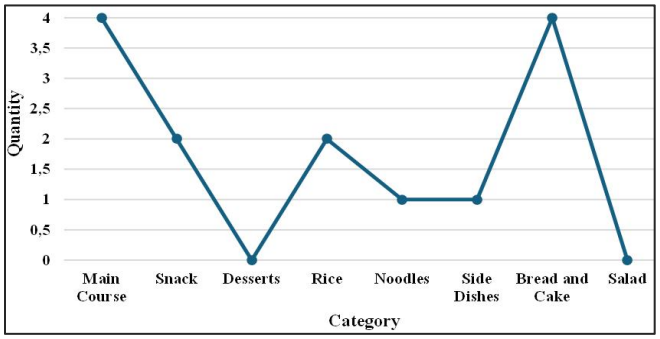

Fig. 7. Quantity purchased by prospective buyer B for each unsold food category.

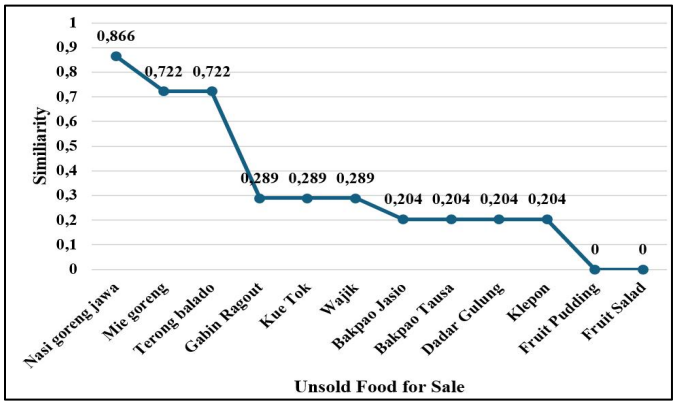

Fig. 8. Similarities between the unsold food categories and prospective buyer A's purchase category history.

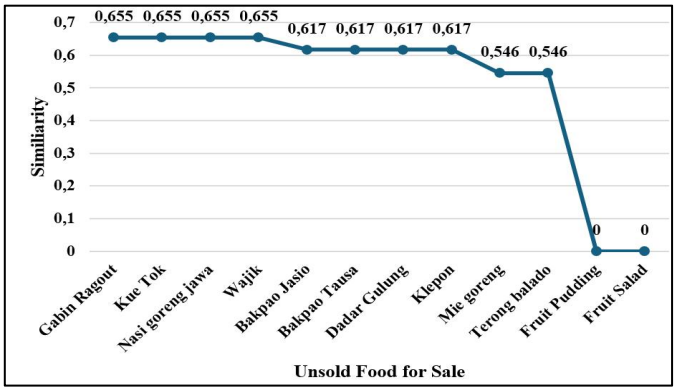

Fig. 9. Similarities between the unsold food categories and prospective buyer B's purchase category history.

Figure 10 shows that the first four recommended surplus food items align with the purchase history of prospective buyer A. The top three recommended items belong to the most frequently purchased category, namely main courses. Of the three recommended main courses, Nasi Goreng Jawa ranks first in purchase volume.

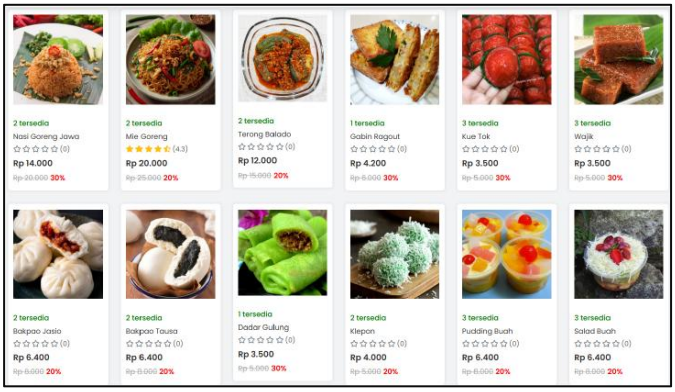

Fig. 10. Recommendation for prospective buyer A.

Meanwhile, Fig. 11 shows that the first 10 recommended items are from the most frequently purchased food categories: bread and cake, and main courses.

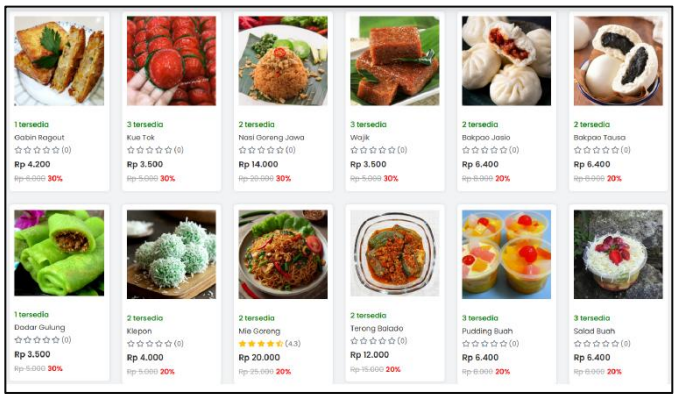

Fig. 11. Recommendation for prospective buyer B.

Table 2 shows that desserts and salad are the most popular surplus food items, followed by main course, bread, and cake. If recommendations are popularity-based, the recommendations for prospective buyers A and B are presented in Table 6. Table 6 shows that fruit pudding, fruit salad, and nasi goreng jawa are the three most popular surplus food items. However, prospective buyers A and B have no history of purchasing fruit pudding or fruit salad. Meanwhile, nasi goreng jawa, which is most frequently purchased by both prospective buyers, ranks third.

A ranking comparison between recommended surplus food items and the purchase history of prospective buyer A is presented in Fig. 12. In contrast, the comparison for prospective buyer B is presented in Fig. 13. Fig. 12 shows that the ranking similarity between the purchase history of prospective buyer A and the recommendation results based on CBF is 150% higher than that of popularity-based recommendations. Similarly, Fig. 13 shows that for prospective buyer B, the ranking similarity with CBF-based recommendations is 300% higher than with popularity-based recommendations. Moreover, the top three CBF-based recommendations for prospective buyers A and B

align with their respective purchase histories. These findings indicate that CBF-based recommendations are more aligned with individual preferences than popularity-based recommendations.

Table 6.
Recommendations for Prospective Buyers A and B

Content-Based Filtering		Popularity
Prospective Buyer A	Prospective Buyer B	
Nasi goreng Jawa	Gabin Ragout	Fruit pudding
Mie goreng	Kue tok	Fruit salad
Terong balado	Nasi goreng Jawa	Nasi goreng Jawa
Gabin Ragout	Wajik	Gabin Ragout
Kue tok	Bakpao Jasio	Kue tok
Wajik	Bakpao Tausa	Mie goreng
Bakpao Jasio	Dadar gulung	Wajik
Bakpao Tausa	Klepon	Terong balado
Dadar gulung	Mie goreng	Bakpao Jasio
Klepon	Terong balado	Bakpao Tausa
Fruit pudding	Fruit pudding	Dadar gulung
Fruit salad	Fruit salad	Klepon

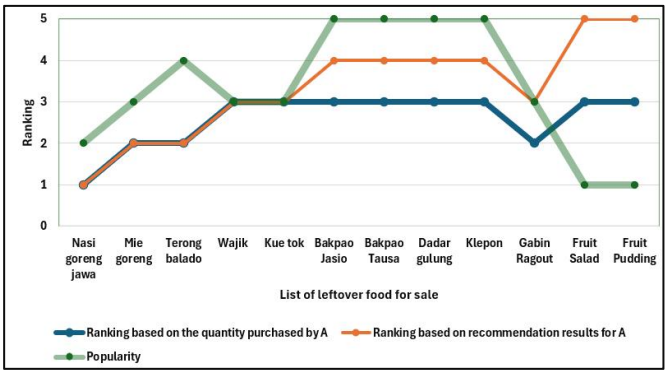

Fig. 12. Comparison between the ranking of recommended surplus food items and the purchase history of prospective buyer A.

Validation of the recommendation feature began by asking respondents to specify their preferred food categories. The first and third respondents favored the snack, bread, and cake categories, while the second respondent preferred the bread and cake categories. Based on each respondent's transaction history over the previous five days, the top five recommendations aligned with their stated category preferences. Therefore, the proposed recommendation system achieved 100% accuracy.

Based on the results of the recommendation feature testing, integrating the marketplace with a recommendation system enables it to continuously learn shoppers' purchasing patterns and adaptively refine its recommendations over time. This capability can improve personalization by reducing the time and effort users spend searching for surplus food items that align with their preferences, thereby increasing the likelihood of a transaction.

The validation results regarding the usefulness and usability of marketplace features from the four business owners showed that the information presented in the marketplace was easy to understand and straightforward to operate. The ability to set the time and discount amount, along with the availability of bargaining features, provides owners with greater control over sales. Other features were also helpful in managing surplus food businesses and expanding market reach to a wider community.

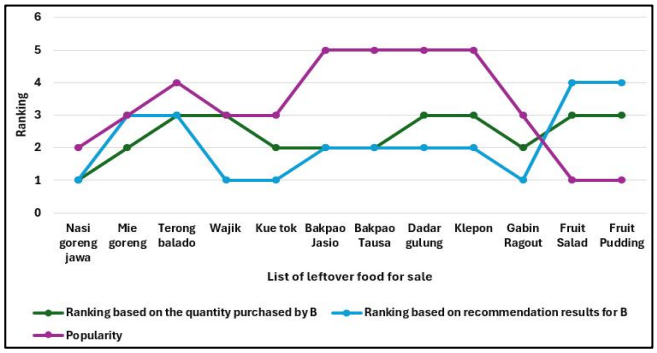

Fig. 13. Comparison between the ranking of recommended surplus food items and the purchase history of prospective buyer B.

The average scores from 15 respondents on the usefulness and usability of the marketplace features are presented in Table 7. The scores are given on a scale of 1 to 5, where 1 indicates very poor and 5 indicates very good. Table 7 shows that the marketplace developed in this study is user-friendly and highly beneficial in practice. Respondents also stated that the recommendation feature is very useful in accelerating the search process, allowing users to order from multiple sellers and reducing the risk of stockout. The bargaining feature also generated interest among respondents in purchasing in larger quantities. However, one respondent suggested adding search criteria based on the seller's name. This phenomenon would be useful to prospective buyers with a strong preference for food from a particular seller.

Table 7.
Summary of Respondents' Feedback

Aspect	Average Score	Standard Deviation
Usefulness	4.673	0.537
Usability	4.707	0.457

To support the respondents' assessment, a one-sample t-test was conducted to compare the sample mean against the hypothesized value, as reported in Table 8. The alternative hypothesis stated that the respondents' mean score was at least 4, indicating that the surplus food marketplace is useful and easy to use.

Table 8.
t-Test: One Population Mean Testing

Description	Value
Hypothesized mean	4
Sample mean	4.67
Sample variance	0.29
#Observations	150
Degrees of freedom	149
Upper critical value	1.66
t-Test Statistics	15.35
p-Value	8.51E-33

With 10 questionnaire items completed by 15 respondents, a total of 150 responses were obtained. The test used a 5% significance level ($\alpha = 0.05$). Table 8 shows that the t-test statistic exceeds the critical value and the p-value is less than α; therefore, the alternative hypothesis is accepted. Based on these

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test results, the surplus food marketplace is confirmed to be beneficial for respondents and easy to use. Finally, validation results from both business owners and the community were positive, indicating that the developed marketplace is feasible for use.

IV. CONCLUSION

Unsold food reduces income and creates waste if not handled properly. One solution to address the problem of unsold food is a marketplace. The marketplace developed in this study integrates a bargaining feature and personalized purchase recommendations, which are the main contributions of this research. The bargaining feature increases shopping interest and helps business owners manage inventory, benefiting both parties. Meanwhile, the recommendation feature accelerates search results based on a user's personalized purchase history

The recommendation feature's test results demonstrate that CBF generates recommendations more in line with user preferences than those based on popularity. Furthermore, validation results show that CBF-based surplus food recommendations, evaluated against users' purchased food categories, achieved 100% accuracy. Meanwhile, the marketplace validation results indicate that it is feasible for both business owners and buyers. The respondents' assessments, scoring 4.71 out of 5 for usability and 4.67 out of 5 for usefulness, support this conclusion.

The criteria used to generate recommendations in this study are limited to the quantity of surplus food purchased in each category, without accounting for potential changes in user preferences over time. For future development, possible improvements include broadening the criteria for making recommendations and adding ways to keep track of changing user preferences. Possible additional criteria to consider include ingredient preferences, preferred sellers, and seller ratings. Additional enhancements could involve features for predicting surplus food demand, forecasting surplus food selling prices, and integrating multiple recommendation methods to enhance recommendation quality.

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