Intelligent decision support model for recommending restaurant
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**Abstract:** People's lifestyles began to change, now they tend to be interested in trying various types of culinary practically. The number of restaurants does not mean someone will visit each restaurant, so it is going to depend on various consideration. Here, an intelligent decision support model was developed to help people to get a restaurant suggestion that suitable for them. Seven parameters were adopted scientifically, i.e. customer interest, price/budget, distance between customer and restaurant, taste rating, cleanliness rating, facilities rating, and halal or nonhalal status. Through using the methods fuzzy logic, cosine similarity distance, selection, and optimization (i.e. hybrid Latin hyper-cube-hill-climbing), model is able to provide restaurant recommendation for individual user or group. In this study, the experiment involved 75 restaurants in Jakarta and eight customers.

**Subjects:** Computational Logic; Computer Engineering; Computer Science; General; Tourism, Hospitality and Events

**Keywords:** Intelligent application; restaurant recommendation; fuzzy logic; hill-climbing; Latin-hyper-cube

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**PUBLIC INTEREST STATEMENT**

Business in the culinary field has grown rapidly in recent years, restaurants are competing to offer a variety of innovative menus. Sometimes, the number of restaurants makes us confused to choose a restaurant that suits our tastes, also looking for a restaurant during rush hour is something difficult. Basically, food is an individual passion that is personalized based on the taste and characteristics of the person himself. Therefore, an intelligent decision support model for recommending restaurant was developed in this study to help users find restaurant that fit their characteristics. Seven parameters were adopted to represent user consideration in choosing a restaurant, i.e. food type, price, location, taste rating, cleanliness, facilities, and status of halal or nonhalal food. Besides helping users, there will be have an impact on increasing restaurant sales that are successfully recommended to the user so that it will also have an impact on increasing business in the culinary field itself.
1. Introduction

In recent years, industrial expansion in the culinary field is growing rapidly, there are many new restaurants that have sprung up and been competing to offer unique menus (Hidayat & Lee, 2018). According to the ministry of tourism and the creative industry, the culinary sector in Indonesia has a large contribution to the country’s income. In 2013, the contribution reached 208.6 trillion rupiah with an average growth of 4.5% (Pratminingsih et al., 2018).

People’s lifestyles began to change and make business in the culinary is quite promising. People now tend to be interested in trying various types of culinary and the number of restaurants does not mean that someone will definitely visit and try each of these restaurants. Decision will depend on various considerations, e.g. type of food, taste, price, restaurant rating, distance, and other aspects.

For most people, choosing a restaurant during a busy time is essentially problematic (Utama et al., 2017). Limited time or maybe congested road conditions must be considered while the restaurant must meet our characteristic. Therefore, an intelligent application to suggest restaurants can be a choice for many people to help them in finding a restaurant that matches their character and taste. Given that people’s lifestyles are starting to shift with the use of technology, the smart application for recommending restaurants can be used as a solution.

The existence of a smart application for restaurant recommendations is going to certainly make it easier for most people who tend to be confused in choosing the right restaurant for them. The habits of people who often rely on the search engine can be replaced by smart applications that are more efficient, as they are able to provide information that matches the character of the user (Zeng et al., 2016). On the other hand, the existence of an intelligent application is also able to provide a positive effect for the restaurant itself. This can have an impact on increasing the number of order at restaurants that were successfully recommended.

Various studies have been conducted by researchers in order to make applications in the culinary sector. For example, Rajmohan et al. (2016) and Adithya et al. (2017) build an online food ordering system. Also, applications to recommend restaurants based on individual users have been carried out by Utama et al. (2017), Isabela et al. (2018), and Utama et al. (2018). On the other hand, Park et al. (2008), Ntoutsi et al. (2012), and Marques et al. (2016) examined applications designed for group-based recommendations. These studies become the evidence that research in the culinary field is fascinating to do.

Talking about Utama et al. (2018) as one study that created a model in this new period, the model is only able to be implemented for individual recommendation. In this paper, (Utama et al., 2018) was expanded to be implemented for group recommendation. Moreover, there are additional parameters that are considered necessarily; such as rating of facilities and status of halal or nonhalal food. The optimization method is also modified from hill climbing to hybrid hyper-cube-hill-climbing (L2HC), since the hybrid method is believed to be able to produce a better number of global optimum value occurrence and give more stable average global optimum value (Elysia et al., 2019).

The novel contribution of the study is a model to support decision maker (in this case is restaurants’ customer) in making decision (both personal and group decision) to select the most proper restaurant based on specific selected parameters. The constructed model called as a decision support model (DSM). The fuzzy logic scientifically operated as a main method in constructing the DSM and also L2HC functioned as an optimizing method to sharp the decision proposed practically. Furthermore, this paper is organized as follows. Section 2 and Section 3 present a related work and research methodology, respectively. Result and discussion are going to be delivered in Section 4. Finally, in Section 5, we conclude the paper and further works.
2. Related work

There are several studies have been done in the culinary field. Zeng et al. (2016) built a restaurant recommendation system using baidu map cloud service and GPS by considering user preferences and location. Model for user preferences can be obtained based on restaurant features that have been visited by user. Furthermore, in determining suitable recommendations, a cosine similarity calculation between user and restaurant features is needed. It also requires distance data of each restaurant against the user's position as a material consideration in recommending suitable restaurants. While Zeng et al. (2016) adopt two parameters, Utama et al. (2017) developed a smart web-based application that was named as “Worth Eat Application” to find restaurants that match customer preferences using three main parameters namely distance, rating, and interest. Fuzzy logic is operated together with bubble-sort to produce recommendations that best suit the user. The research was further developed into android-based application called “Worth Eat II” (Utama et al., 2018). The parameters in the previous study were modified by adding food price parameters and dividing the rating parameters into two parts, namely taste and cleanliness. Fuzzy method is applied together with Euclidean distance to produce fittest value while the optimization method uses hill climbing. The results show that the use of hill climbing can shorten the time in searching for the best solution. Indeed, this continuing study is done based on the previous studies (Utama et al., 2017) and (Utama et al., 2018). The significant added-work is on optimizing method L2HC implementation, in group decision modeling, and new added parameters (i.e. facilities rating and halal status).

In addition, Park et al. (2008) used Bayesian network to model the preferences of individual users and combined them with analytic hierarchy process method to provide recommendations for group. The criteria operated methodically consist of the type of restaurant, price, mood, and distance. Group recommendations for restaurants were also examined by Ntoutsi et al. (2012). The approach taken was using collaborative filtering for personal recommendations, looking for similarities between user A and other users, where the greatest similarity will be used as a reference to recommend items to user A. Then, for group recommendations by aggregating recommendations from all members in the group and made into a list of recommendations. Something similar is also applied to research (Marques et al., 2016). Where in the process of recommending the system will provide five lists of restaurant with the highest output value, then each user will be asked to choose five choices from the existing list. Most choices will be chosen as the final result of the restaurant recommendation. Finally, also several studies relating to topic decision making with operating other methods were done; such as Abbate et al. (2014), Calza et al. (2015), D’Aniello et al. (2016), and Gaeta et al. (2017).

3. Research methodology

The research involved five stages as shown in Figure 1. In the initial stage, we defined the problem and conducted a literature study by looking for papers that are closely related to this research. After conducting a preliminary study, the parameters that going to be benefitted in this study were chosen. In determining parameters, we have examined more deeply what parameters can be used in making a decision support model for recommending restaurants and finally decided seven parameters to be used; i.e. interest, price, distance, taste rating, and cleanliness rating (Utama et al., 2018), and two others are facilities rating and halal or nonhalal status.

By providing facilities, a restaurant is able to attract more customers. As example, the existence of Wi-Fi connection as a facility is able to influence purchasing decisions (Lopez, 2018). Therefore, offering attractive facilities can influence user's decision in choosing a restaurant. Also, status of
halal or nonhalal was selected because most of the population in Indonesia is Muslim. Muslim customers are very sensitive to the products they consume. It means the availability of halal food is very demanded by Muslims. Based on Islamic law, Muslim adherents are not allowed to consume pork or meat of animals that die first before being slaughtered (Battour & Ismail, 2016).

In the second stage, the restaurant data were collected through observation on the Zomato website (Zomato, 2019) (i.e. type of food, price, location, and taste rating) and analysis based on customer reviews or restaurant photos to fulfill data of cleanliness rating, facilities rating, and halal status. Furthermore, other method such as questionnaire is used to get customer data and determine weights for the objective functions to produce a recommendation result. Here, 75 restaurants and eight customers were recorded to be used in the experiment. Data of restaurants are taken in five regions of Jakarta, where in each region (Central Jakarta, West Jakarta, East Jakarta, North Jakarta, and South Jakarta) 15 data were collected. In the next stage, parameter such as price, distance based on customer and restaurant location will be processed using a simple fuzzy logic while all rating parameters processed using fuzzy rule based. This fuzzy processing result later will be used as input data in the model.

Before developing the model, it is necessary to have the stage of making a design of the model. In this case, a unified modeling language (UML) consisting of two diagrams, i.e. class diagrams and activity diagrams will be performed. Where, the UML is a modelling language operated scientifically to speak the constructed model to common reader in easy way. Last stage, three methods were operated. They were simple selection logic, cosine similarity distance, and optimization using L2HC method. A simple selection logic is used to sort out the status of halal or nonhalal food. Cosine similarity distance is applied to calculate the similarity between customer interests and types of food in each restaurant, while L2HC method is used to optimize the best restaurant recommendation by adjusting customer’s budget.

4. Result and discussion

4.1. The constructed model and experimental result
In our constructed model, seven parameters are officially applied as a material consideration to give the suitable restaurant recommendation. Five parameters of previous research (Utama et al., 2018) that are interest, price, distance, taste rating, and cleanliness rating were combined with two new parameters namely facilities rating and halal or nonhalal status. Here, interest refers to the type of foods that is liked by the customer, while parameter price represents customer usual budget spent when visiting a restaurant. Data for restaurant and customer locations are stored in longitude and latitude coordinates. These coordinates must be preprocessed using Google Maps API to produce distance in kilometer unit. Three types of parameter rating, respectively, denoting online taste rating, cleanliness rating, and facilities rating. Also, there is halal and nonhalal status to filter out nonhalal restaurant for exclusively Muslim customers.

The value of five parameters is converted using fuzzy-defuzzification process. Detail of triangular membership function (TMF) and linguistic variables benefited in this study can be shown in Figure 2. TMF for price, taste, and cleanliness parameter is already researched by Utama et al. (2018). Facilities rating is also something similar with taste and cleanliness rating, thus its TMF will be identical with other rating TMF. For distance parameter, the TMF is made based on the analysis of distance data used in this study which is then divided into five linguistic variables, they are too close, close, standard, far, and too far. Price and distance parameters are processed using simple fuzzy logic and defuzzification using weighted average method in Equation (1). Z is centroid of each of the membership function while \( \mu (Z) \) refers to membership values. For all rating parameters, fuzzy rule based (code 1) were implemented. To simplify code 1, linguistic variables of each rating parameter will be normalize into four types of terms: they are bad, pretty, good, and very good (Table 1). This rule based will convert the
Figure 2. Triangular membership function configuration.

Table 1. Term normalization

| Term    | Taste     | Cleanliness | Facilities |
|---------|-----------|-------------|------------|
| Bad     | Tasteless | Dirty       | Bad        |
| Pretty  | Pretty    | Pretty      | Pretty     |
| Good    | Delicious | Clean       | Good       |
| Very Good | Very Delicious | Very Clean | Very Good |

rating value into distance with value \([0, 1]\). If restaurant had a better rating then the distance, it will be smaller and vice versa.

\[
Z' = \frac{\sum \mu(Z) \cdot \tilde{Z}}{\sum \mu(Z)}
\]  

(1)
Additionally, class diagram is provided in Figure 3. The diagram is telling about interconnected entities in the model. The entities are symbolized via class. Class Customer has one aggregated class that is CustomerLocation. While, Class Restaurant has six aggregated classes, i.e. Category, FoodPrice, RestaurantLocation, RestaurantStatus, Rating, and Recommendation. Here, TasteRating, CleanlinessRating, and FacilitiesRating are derived from class Rating. After creating the class diagram, we proposed the workflow/flowchart of the model in Figure 4.

![Class Diagram](image)

### Code 1. Rule Based for Ratings

```
Rating → Distance:
IF (Rating = Bad) or (Rating = Pretty)
    Then (Distance = Long)
ELSE IF (Rating = Pretty) or (Rating = Good)
    Then (Distance = Medium)
ELSE IF (Rating = Good) or (Rating = Very Good)
    Then (Distance = Short)
```

After parameterizing, data are ready to be processed to produce the fittest restaurant. Cosine similarity (Zeng et al., 2016) was implemented to calculate distance between customer's interest and restaurant's features (type of food). Equation for cosine similarity is written in Equation (2). Hereafter, we must process the last parameter that is halal or nonhalal status using selection method. It has a value of “Yes” for customer who can consume halal food only or “No” for customer who can consume both halal and nonhalal food. This status will be used to sort out nonhalal restaurant for customer that prefers halal food. After processed all parameter, it is time to calculate the recommendation. The weight of each variable in the objective function is obtained based on user opinion when answering the questionnaire. There are 88 randomly chosen user opinions to fill in the questionnaire and finally the decision value is obtained through Equation (3); where A is a taste value, B is denoting a cleanliness value, C represents a facilities value, X signifies a food interest value, Y is a price value, and Z is symbolizing a geographical distance value. Detail of weight distribution is described in Figure 5.

Based on the model established, we simulated eight customers and 75 restaurants as our data and here the model is able to generate the decision alternatives for all customer. Likewise, the optimization process is able to provide results with better objective function value than before by adjusting customer’s budget. We present the comparison of alternative result without optimization and alternatives result using optimization in Figure 6. This optimization will minimize the distance
generated from budget parameter. The results of recommendations and data examples are presented in Table 2. Each box with a bold border consists of three data, respectively, are customer data, the alternative of a restaurant that was successfully recommended without optimization process, and the alternatives of a restaurant after the optimization is applied by adjust the budget parameter.

Concerning optimization process, it is going to give a better decision value by minimizing Equation (3); thus the objective function could be written as Equation (4), where the decision parameter that should be played is \( Y \) or budget (from customer side) with its constraint in between 0 and 100 (in 1,000 Rupiah). The optimizing process result is able to change the decision alternative. However, other parameters besides the budget have a weight that plays a significant role in producing the value of the objective function. Therefore, if customers are more flexible with their spending budget, other parameters are able to produce other decision alternatives that are better, or maybe the same alternative but has a smaller objective function value after they change their budget.
Lastly, for group recommendation, we aggregate each objective function value from each customer member in that group. There are two groups (Table 3) to be tested, first group consists of customers 1, 2, and 3; while customers 6 and 7 will be in the second group. Result showed that restaurant 11 is suitable for the first group and restaurant 72 for the second group. Actually, in the first group, customer 1 and customer 2 have a close distance to restaurant 9. But however, customer 3 must consume halal food therefore the recommendation does not allow restaurant 9 to be visited by group 1 because it offers nonhalal food. Therefore, the recommendation results show that restaurant 11 is more suitable to be visited.

The second group is recommended to visit restaurant 72. Although the results of the two recommendations individually do not lead to restaurant 72, it does not mean closing the possibility if the results of the recommendation are outside the results of individual recommendations. It can be happened because when they become a group, the model will suggest restaurants with the smallest average objective value of all members in the group.
| Customer/Restaurant | Interest | Budget/Price (Rupiah) | Distance (Kilometer) | Taste (0–5) | Cleanliness (0–5) | Facilities (0–5) | Halal status |
|---------------------|----------|----------------------|----------------------|-------------|------------------|-----------------|-------------|
| C1                  | Indonesian, Chinese, Steak, Western, Street Food | 40,000 | 375,000 | 5.0 | 5.0 | 5.0 | No |
| R9                  | Italian, Western | 40,000 | 11.7 | 3.5 | 3.7 | 4.3 | No |
| R72                 | Street food, Dessert, Korean, BBQ, Western, Coffee, Seafood, Chinese, Padang, Grill, Sushi, Steak | 40,000 | 150,000 | 5.0 | 5.0 | 5.0 | Yes |
| C2                  | Italian, Western | 40,000 | 150,000 | 5.0 | 5.0 | 5.0 | No |
| C9                  | Italian, Western | 40,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| R8                  | Indonesian | 40,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| R72                 | Indonesian, Fast food, Soto, Padang | 40,000 | 150,000 | 5.0 | 5.0 | 5.0 | Yes |
| C3                  | Fast food, Soto, Korean, Padang, Meatball, Chinese, Noodle | 40,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| C4                  | Chinese, Indonesian, Fast food, Noodle, Soto | 50,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| R2                  | Street food, Korean, Japanese, Asian, Fast food, Soto, Padang, Meatball, Chinese, Noodle | 50,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| C6                  | Fast food, Soto, Padang, Meatball, Chinese, Noodle | 50,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| C7                  | Street food, Korean, Japanese, Asian, Fast food, Noodle, Soto | 50,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| R3                  | Indonesian, Fast food, Soto, Padang | 50,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| C8                  | Street food, Indonesian, Snack, Seafood, BBQ, Grill, Korean, Padang | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| C9                  | Street food, Indonesian, Snack, Seafood, BBQ, Grill, Korean, Padang | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| R2                  | Fast food, Soto, Padang, Meatball, Chinese, Noodle | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| C1                  | Indonesian, Chinese, Steak, Western, Street Food | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| R8                  | Indonesian, Fast food, Soto, Padang | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| R72                 | Indonesian, Fast food, Soto, Padang | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| C3                  | Fast food, Soto, Padang, Meatball, Chinese, Noodle | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| C4                  | Street food, Korean, Japanese, Asian, Fast food, Soto | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| R2                  | Indonesian, Fast food, Soto, Padang | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| C1                  | Indonesian, Chinese, Steak, Western, Street Food | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| R8                  | Indonesian, Fast food, Soto, Padang | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| R72                 | Indonesian, Fast food, Soto, Padang | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| C3                  | Fast food, Soto, Padang, Meatball, Chinese, Noodle | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| C4                  | Street food, Korean, Japanese, Asian, Fast food, Soto | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
| R2                  | Indonesian, Fast food, Soto, Padang | 60,000 | 375,000 | 5.0 | 5.0 | 5.0 | Yes |
similarity \( (A, B) = \frac{A \cdot B}{\| A \| \times \| B \|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}} \) \hspace{1cm} (2)

\[ f(A, B, C, X, Y, Z) = 0.182X - 0.177Y + 0.144Z + 0.19A + 0.183B + 0.124C \] \hspace{1cm} (3)

\[ \min f(Y) = 0.182X - 0.177Y + 0.144Z + 0.19A + 0.183B + 0.124C \] \hspace{1cm} (4)

4.2. Discussion

“Worth Eat II” (Utama et al., 2018) has been developed as an intelligent model for recommending restaurant based on individual user using five parameters. It used a fuzzy logic, Euclidean distance, and optimization using hill climbing. Here, they research is expanded to be able produce recommendation for group (Ntouisi et al., 2012; Marques et al., 2016). Two new parameters are added, fuzzy logic is also modified using fuzzy rule based. Cosine similarity distance (Zeng et al., 2016) to calculate distance between customer’s interest and restaurant’s type of food features is combined into this model. Optimization method using L2HC by adjusting customer’s budget will provide the best decision alternative while (Utama et al., 2018) use hill climbing to decrease searching time. In addition, we use more data consisting of 75 restaurants and eight customers to be tested in this research.

5. Conclusion

An intelligent decision support model was successfully created. It was able to provide a recommendation based on individual or group user. We adopt seven parameters, i.e. interest, price, location, taste rating, cleanliness rating, facilities rating, and halal or nonhalal status. Fuzzy logic, cosine similarity distance, selection, and optimization using L2HC methods were operated to construct the model. Fuzzy logic can eliminate the uncertainty judgment of parameter values, cosine similarity distance for determining the degree of similarity between customer’s interest and restaurant’s feature, selection to filter out nonhalal restaurant for Muslim customer, and L2HC provide best decision alternative if customer want to compromise with their budget.

For the future, researching new parameters that suitable for restaurant recommendation is quite interesting. The parameters such as eating time behavior can influence the decisions. When will someone consume snack, tea, or coffee? Moreover, in this study, customer’s interest is still a static data. Maybe it can be modified into dynamic. Customer’s interest can be changed or updated if customer visits a restaurant that does not suit their interest. Something like this will be more exciting and challenging to study.

Table 3. Group recommendation result

| Group | Alternative result → Aggregated value | Customer | Objective value on alternative restaurant |
|-------|-------------------------------------|----------|------------------------------------------|
| Group 1 | R11→0.3884496                       | C1       | 0.413002                                 |
|        |                                    | C2       | 0.436393                                 |
|        |                                    | C3       | 0.315955                                 |
| Group 2 | R72→0.3566771                       | C6       | 0.322978                                 |
|        |                                    | C7       | 0.390376                                 |

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