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A Proposed Classification Method in Menu Engineering Using the K-Nearest Neighbors Algorithm

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***Abstract*— In the culinary business, the menu is crucial; therefore, the performance of each menu needs to be known to maintain business continuity. Menu engineering is a special technique used to see the performance comparison of each menu item. This research proposes modeling menu engineering with a new approach in classifying menu items using the k-Nearest Neighbors (k-NN) algorithm using the sales training data of sales data in 2019 belonging to one of the micro, small and medium-sized enterprises in the culinary sub-sector in Salatiga, Indonesia. In the modeling, the popularity index (menu mix) and item contribution margin are used as variables, while the menu item class is used as the label attribute of the classification. Determination of the k value in the k-NN algorithm was done by the experimental method so that it produces the most optimal k based on the highest accuracy value, while the distance calculation on k-NN was done using euclidean distance. Evaluation of the model was done using 10-fold cross-validation with four performance evaluation criteria, namely weighted mean recall, weighted mean precision, accuracy, classification error. Based on the evaluation results, an accuracy of 96.84% was obtained; thus, the proposed model is considered to have given good and accurate results. This proposed model has been implemented in MSME sales data to classify menu items. The results of this classification were used as a basis for recommending menu engineering strategies to MSMEs.**

***Keywords*— Menu engineering; k-NN; classification; 10-fold cross-validation.**

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I. INTRODUCTION

Culinary is one of the sustaining mainstays of Indonesia's tourism sector and creative economy [1], [2] with a contribution of 41% of the total revenue of the tourism sector and creative economy in 2017 [3]. This can also be seen from the employment in the culinary industry, which is the second-highest in the creative industry reached 29.17% [4]. This confirms that culinary plays an important role in job creation and economic growth [5]. However, the culinary industry is a very competitive environment, resulting in a failure rate of close to 60% in the first three years of opening [6], where one of the causes is poor menu choices [7]. In the culinary business, the menu is a crucial matter, where it is a core product [8], [9] which largely determines how operations will be organized and managed, also controlling many aspects of the culinary business [10], [11]. Therefore the performance of each menu needs to be known to maintain business continuity.

Menu engineering is a special technique used to see the performance comparison of each menu item [12], [13]. By knowing the menu's performance, it is possible to estimate future sales [14] so that an appropriate design and marketing strategy can be determined. Menu engineering can help improve managerial effectiveness, create menu contents and the structure of menu prices, which must be very well planned [15]. This, in its implication, can maximize restaurant profits [14]. Thus, the right engineering menu is very important for business success [16].

In menu engineering, sales history data is needed for analysis. Some elements of the required sales data are menu prices, cost of goods sold, profits, and menu popularity index. This research proposes a menu engineering model using the k-Nearest Neighbors (k-NN) algorithm, which is an instance-based learning algorithm [17]–[20] that can identify groups of data by looking at similar historical behavior represented with the value of neighbors proximity [21]–[26] and then validated by a large number of neighbors [27] on the dependent variable.

With k-NN, a simple and effective classification method [28], modeling of menu item classification based on popularity index and contribution margin [29]–[31] is done using training data, where the results can be used as a basis for classifying new menu items in the test data. The process is done by calculating the distance of the menu item points on the test data with the menu item points on the training data using the Euclidean formula [32]. The model result is expected to more dynamically and accurately help group menu performance because it is based on the closest distance to the history of classifying menu items.

II. MATERIAL AND METHOD

The menu engineering concept was introduced by Kasavana and Smith, who grouped menu items in four quadrants formed from a 2x2 matrix based on the intersection of the popularity index and contribution margin [29], [33], [34] as shown in Fig. 1.

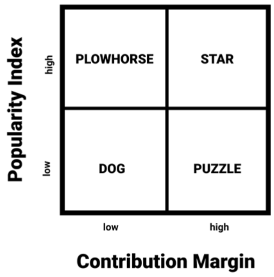

Fig. 1 Menu Engineering Matrix

The contribution margin is the result of reducing the sale price of menu items with the cost of menu items, while the popularity index or menu mix is the number of the item sold in the menu divided by the total number of items sold of all menus stated in percentage [29], [35]. The contribution margin (CM) formula and the popularity index (MM) are seen in Formulas (1) and (2).

$$CM = Item\ Price - Food\ Cost \quad (1)$$

$$MM\% = \frac{number\ of\ the\ item\ sold}{total\ number\ of\ items\ sold} \times 100\% \quad (2)$$

Menu engineering has been widely used as an approach in analyzing menus [36], [37]. In addition, several studies have carried out modeling of the menu engineering with a different approach, such as LeBruto *et al.* [38]., who inserted labor into the model, so the matrix becomes 3x2 and produces eight quadrants. In addition, Horton also included labor estimates in the contribution margin [39]. In 2017, Tom and Annaraud [16] applied the fuzzy multi-criteria decision making (FMCDM) technique to model the engineering menu into nine quadrants. Setiyawati and Bangkalang also modeled menu engineering using a two-step cluster by adding one category variable, namely the item category, to see the dominant menu categories in each later formed cluster [31].

In this research, menu engineering modeling was done using k-NN. The stages in this study can be seen in Fig. 2, which consists of 3 main stages, namely: 1) Pre-processing; 2) k-NN model; 3) Strategy Recommendations.

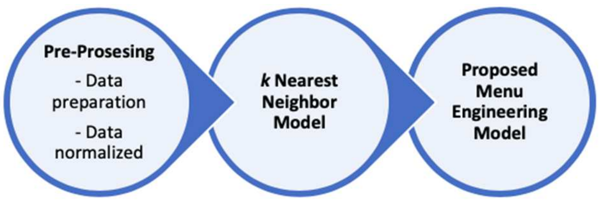

Fig. 2 Research Stages

A. Pre-Processing

The initial data set used in this study was sales data of one of the micro, small and medium enterprises (MSMEs) in the culinary field in Salatiga, Indonesia, in the period of August-December 2019, which had 120 menu items and 73,008 transaction data. The variables used in the proposed menu engineering model are the popularity index (menu mix) and item contribution margin, and the menu item class as the label attribute of the classification.

There were differences in the range of attributes in the popularity index variable and item contribution margin, so data transformation was needed [40]. The data transformation method in this modeling used Z-score normalization, a method for normalizing data based on the average distribution and distribution of data in the sample [41], [42]. The Z-Score Normalization formula is seen in Formula (3).

$$xb = \frac{\text{xa} - \bar{\text{x}}}{\sigma} \quad (3)$$

Where:
xb = new value
xa = old value
$\bar{x}$ = average
σ = standard deviation

The purpose of this value transformation is so that the minimum or maximum values of the resulting data are standardized and at the same attribute range to produce more accurate calculation results. Normalization results from the data set are shown in Table 1.

TABLE I
NORMALIZATION DATA SET

Item Code	Popularity Index %	Item C.M.	Menu Item Class
1	-0.385	-0.579	DOG
2	-0.279	-15867	DOG
3	-0.172	147251	PUZZLE
4	-0.289	0.4654	PUZZLE
5	-0.524	0.7029	PUZZLE
…	..	…	
120	0.1314	-11440	DOG

B. k-Nearest Neighbors Model

To obtain a good and accurate processing model, an evaluation of the model must be made. This study used k-fold cross-validation as a model evaluation method. k-fold cross-validation is one method that is often used to evaluate models or algorithms [42], [43]. The higher the k-fold value can reduce the level of bias of the performance estimator, and the variant of the performance estimator increases; thus, the algorithm's output is more accurate and has more variability [42]. The main idea in the k-fold cross-validation method is to divide the sample data into the same set of k-fold where *k* is the number of data sharing partitions [44]. K-fold used in evaluating this model was 10-fold, so the data was divided into ten partitions, which means nine partitions were used as training data and the rest as testing data. Training data was carried out ten times using different training partitions and testing data. To calculate the performance of this model, the total average performance of each partition experiment was calculated. Fig. 3 shows the stages carried out to evaluate the model being built.

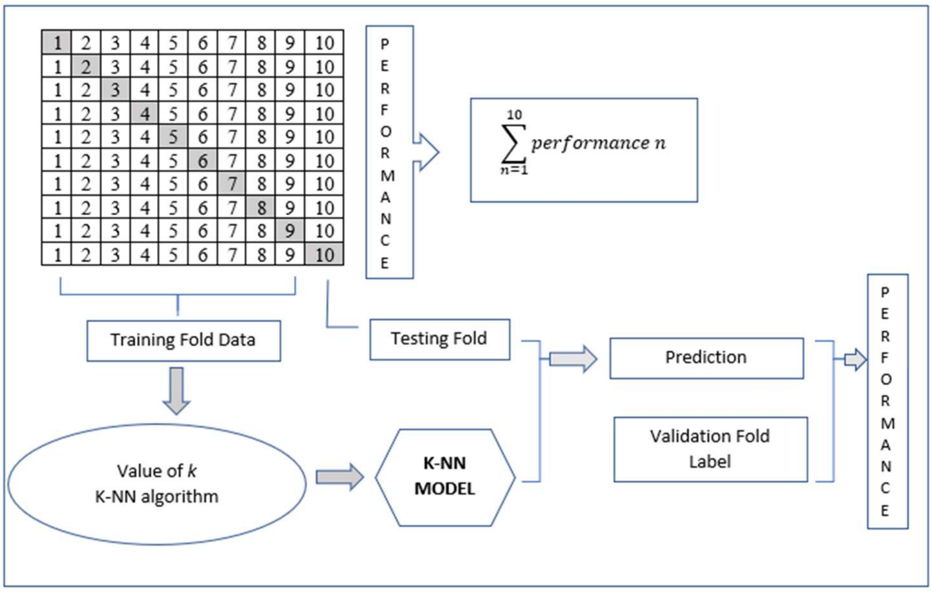

Fig. 3 Model Evaluation Stages

In Fig. 3, after the division of training fold data, the k value was determined, which is the number of nearest neighbors in which it is the basis of the classification on the k-NN algorithm [27], [45]. So that the determination of the optimal *k* value, in this case, means that *k* has the highest accuracy, can produce an accurate classification. The determination of the *k* value in this study used an experimental method with k-fold cross-validation [46]. The experiments carried out resulted in performance, as shown in Table 2.

TABLE II
EVALUATION VALUE OF *K*

No	Value of *k*	Accuracy
1	3	92.50%
2	5	93.33%
3	7	93.33%
4	9	92.50%
5	11	91.67%
6	13	91.67%
7	15	91.67%
8	17	90.83%
9	19	90.00%
10	21	90.83%

Based on Table 2, out of 10 trials using different k values, the highest k accuracy obtained was at values $k = 5$ and $k = 7$. Because the highest accuracy was in the two *k* values, an experiment was conducted on both values to choose one *k* value. The test results found that the highest accuracy was at $k = 5$.

The k-NN algorithm uses distance calculation for the formation of the nearest neighbors. The distance calculation method used was Euclidean distance, which measures two distances at different points [47]. The Euclidean distance equation is seen in Formula (4).

$$D(i,j) = \sqrt{(X_{1i} - X_{1j})^2 + (X_{2i} - X_{2j})^2 + \cdots + (X_{ki} - X_{kj})^2} \ldots \quad (4)$$

In Formula 4, *D(i,j)* is the distance of data to *i* to the central point *j*, X_{ki} is the data to *i* on the attribute data to *k*, and X_{kj} is the center point to *j* on the attribute to *k*. Data grouping was done by entering data D(i,j) in a Class category according to the number of the *k* nearest neighbors, where the determination of k-nearest neighbors is seen from the order of the shortest distance.

III. RESULT AND DISCUSSION

A. Model Menu Engineering Proposal

Menu Engineering is a tool that can be used to compare the performance of each menu item and help MSME gain valuable insight into MSME menu to make more strategic business decisions. In the menu engineering, the menu is categorized into four categories which are STAR, PUZZLE, PLOWHORSE, and DOG. This study proposes the modeling of menu engineering with a new approach in classifying menu items using the k-NN algorithm. Table 3 results from the accuracy prediction on each menu item class, where the class represents a category from the menu engineering model in this study.

TABLE III
ACCURACY TABLE

	DOG	PUZZLE	STAR	PLOWHORSE	Class Precision
Prediction DOG	52	3	0	0	94.55%
Prediction PUZZLE	1	56	3	0	93.33%
Prediction STAR	0	0	0	0	0.00%
Prediction PLOWHORSE	1	0	0	4	80.00%
Class Recall	96.30%	94.92%	0%	100.00%	

Based on Table 3, the accurate prediction of each item class is obtained according to precision and recall. Precision and recall are calculations to determine how accurately the algorithm produces correct predictions. Precision is the probability of the correct prediction given by the algorithm, while recall is the probability of a correct prediction identified according to each menu item class [48], [49]. In other words, class precision is the correct item prediction ratio compared to all the prediction results that correspond to that class. At the same time, class recall is the correct item prediction ratio compared to all actual results for the class.

The result obtained in Table 3 shows that the dog category has a class precision of 94.55%. This means, of the 55 predicted menu items on the class dog, there are 52 corresponding menu items. As for the class recall has a performance of 96.30%, which means that of the 54 actual menu item data on the class dog, there are 52 corresponding prediction results. The puzzle category has 93.33% class precision and 94.92% class recall, items in the star category have 0% class precision and class recall, and articles in the plowhorse category have 80% class precision and 100% class recall. K-fold cross-validation performs iterations as many as the number of k values, resulting in different performance outputs. Table 4 is an evaluation of the average performance of the proposed model.

TABLE IV
MODEL PERFORMANCE EVALUATION

Criteria	Micro Average
Weighted Mean Recall	98.33%
Weighted Mean Precision	87.08%
Accuracy	96.84%
Classification Error	3.16%

Table 4 is the result of evaluating the average performance of the algorithm being modeled. Evaluations using 10-fold cross-validation are based on some criteria. The first criterion is weighted mean recall. The average obtained from the weighted mean recall is 98.33%, so it can be concluded that the probability of the predicted value of the actual data is very good. The next criterion is weighted mean precision. This algorithm model's average weighted mean precision is 87.08%, so the item prediction probability is considered good. Then another criterion is the accuracy value. The accuracy value of the proposed algorithm is 96.84%, and the classification error is 3.16%.

Based on the performance evaluation in Table 4, algorithm modeling is considered to have given accurate results. With this basis, a model was implemented on the MSME sales data. The data set used as input data was menu sales data in January-March 2020, with a total of 95 menu items. The results of this classification were used as a basis for recommending menu engineering strategies to MSMEs. The classification results obtained are seen in Table 5.

TABLE V
OUTPUT MENU ENGINEERING USING K-NN MODEL

Item Class	Item Code
STAR	18,67,71,89
PUZZLE	3,6,11,21,22,25,26,27,31,32,33,34,37,38, 39,41,42,43,44,45,46,47,48,51,53,57,58, 59,60,61,62,66,70,72,73,74,81,82,83,84, 85,86,90,92,93,95
PLOWHORSE	16,23,69
DOG	1,2,4,5,7,8,9,10,12,13,14,15,17,19,20, 24,28,29,30,35,36,40,49,50,52,54,55, 56,63,64,65,68,75,76,77,78,79,80,87, 88,91,94

Table 5 is the result of menu engineering classification based on the proposed modeling. Based on the classification results, there are four menu items in the STAR class. In the PUZZLE class, there are 46 menu items. The PLOWHORSE class has three menu items, while the DOG class has 42 menu items. Based on the results of the classification of each menu item, MSMEs can choose strategies that can be used to increase business profits by applying strategy to menu engineering.

B. Menu Engineering Strategy

1) STAR: STAR classification has a high popularity index and provides high contribution margins [29], [35]. Some strategies that can be applied in the STAR classification are as follows:

- Maintaining the quality of the menu, portions, and appearance according to the applicable recipe standards [16], [36]
- Increasing the selling price periodically by taking into account the increase in existing demand and the selling price of competitors [31].
- Customers tend to order items that "stand out", so menus in this classification can be placed in the visible section.

2) PUZZLE: PUZZLE classification is a menu with a low popularity index but gives a high contribution margin [29], [35]. Referring to these conditions, several strategies must be implemented so that the menus become more popular while still ensuring that the contribution margin does not become low. The strategies that can be applied are as follows:

- Putting menu information in the most visible part to attract customer attention [16].
- Lowering prices while still paying attention to appropriate pricing strategies such as profit margin conditions, cost of goods sold, and competitors' selling price.
- Give discounts on food delivery applications and/or promote the menu through social media to attract customers [31].
- Offering larger portion sizes [37] or providing "add-ons" to increase the menu item's value.

3) PLOWHORSE: The PLOWHORSE classification contains menus with a high popularity index but gives a low contribution margin [29], [35]. Therefore, efforts must be made to increase the benefits of this classification. Some strategies that can be applied in the PLOWHORSE classification are as follows:

- Increasing the selling price of food gradually by taking into account the number of requests [36].
- Reducing food costs, such as reducing the number of ingredients orders, efficiency of menu processing, reducing portion sizes [36], [37] or simplifying presentation while maintaining the quality and aesthetic appearance of the food.
- Seeing that this classification consists of menus favored by many customers, these menus can be placed far or hidden from the focal point of the menu to attract customers to more profitable menus [36].

4) DOG: The DOG classification contains menus with a low popularity index and contribution margin [29], [35], or it can be said that the DOG classification is menus that are not popular and unprofitable. Some things that can be applied for menus in the DOG classification are as follows:

- Removing or eliminating the menus. This is highly recommended to reduce substantial business burden [31].
- Minimizing the number of menus in this classification as much as possible. This can be interpreted as an effort to move the menu to another classification. For example, transferring it to the PLOWHORSE classification by increasing its popularity by creating menu packages from this classification combined with foods or drinks from other classifications with high popularity.

IV. Conclusion

This study proposes the modeling of menu engineering with a new approach in the classification of menu items using the k-NN algorithm. The training data used was the MSMEs sales data in 2019. Model evaluation was done using 10-fold cross-validation with four performance evaluation criteria: weighted mean recall, weighted mean precision, accuracy, and classification error. Based on the evaluation results, 98.33% weighted mean recall is obtained with 87.08% weighted mean precision and 96.84% accuracy, so that the proposed model is considered to have given good and accurate results. The classification results of the menu engineering implementation with the proposed model can be used to provide strategies to MSMEs in managing prices, product marketing, etc., to increase MSME business profits.

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