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Application of K-Nearest Neighbor Algorithm for Consumer Behaviour Identification and Product Personalisation Based on Big Data Analysis

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ABSTRACT

The rapid digital transformation has fundamentally altered the retail industry, presenting challenges such as shifting consumer behavior and intensified market competition. This research explores the application of the K-Nearest Neighbor (KNN) algorithm for identifying consumer behavior and developing product personalization systems based on big data insights. Utilizing a dataset comprising 10,000 transaction records from January to December 2023 and 5,302 product types, we implemented the KNN algorithm to predict consumer purchases. The data was processed into 89,908 distinct transaction records. Our evaluation, using 5-fold cross-validation, demonstrated that the optimal performance of the KNN model was achieved with k=10, yielding a precision of 0.8319, recall of 0.8311, and an F1-score of 0.8312. These findings highlight the effectiveness of KNN in enhancing consumer satisfaction through precise product recommendations. This study provides strategic insights for modern retailers aiming to leverage AI and big data to remain competitive and meet evolving consumer expectations.

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1. INTRODUCTION

The digital era has fundamentally changed the landscape of the retail industry, with rapid changes in consumer behavior and increasingly fierce market competition being the two main challenges [1-3]. Modern consumers want a more personalized, fast, and convenient shopping experience, triggering the need for continuous adaptation of retail businesses [4,5]. In this context, the use of Artificial Intelligence (AI) and big data analysis has become very relevant. These technologies offer the ability to understand and respond to consumer behavior more accurately and in a timely manner, enabling personalization of products and services that can improve the shopping experience and customer satisfaction [6-8]. This research aims to explore the potential of AI in identifying consumer behavior and developing a dynamic product personalization system based on big data insights. The urgency of this research lies in the urgent need of the retail industry to adapt to the rapid changes in consumer behavior and the intensification of market competition [9-11]. Without the use of technologies such as AI and big data, modern retail struggles to meet evolving consumer expectations, potentially losing market share and relevance [12,13].

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Some of the main problems that need to be addressed in the modern retail industry include a lack of understanding of consumer behavior, limited product personalization, inefficient data processing, and fierce market competition. Previous research has shown that the use of AI and big data in the retail sector can provide various significant benefits. For example, research by Sathyanarayana (2023) shows that big data analysis can improve understanding of consumer spending patterns and predict future needs [14]. Meanwhile, research by Krishnareddy et al. (2022) highlights how the implementation of AI in product personalization can improve customer satisfaction and loyalty levels [15].

This research is expected to provide strategic insights and practical solutions for the retail industry in utilizing technology to improve consumer satisfaction, as well as optimizing operations and marketing strategies. The development of innovative AI models and effective personalization systems is the main focus of this research. Using the K-Nearest Neighbors (KNN) method, this study offers a new approach in identifying consumer behavior that is more accurate and responsive to changes in shopping patterns. The advantages of this research include the use of the KNN method which is known for its high classification ability and flexibility in various types of data, a big data approach that provides deeper and more accurate insights into consumer behavior, innovations in product personalization that can be adjusted to specific consumer needs in real-time, and industry relevance that provides practical solutions that can be implemented by retail business actors to increasing competitiveness and sustainable growth in the digital era. Thus, this research is expected to help the modern retail sector in facing the challenges of the digital era, strengthening competitiveness, and encouraging sustainable growth.

2. RESEARCH METHOD

The development of a recommendation system requires several important stages to ensure that the data can provide accurate prediction results. This process includes data collection and processing, as well as the application of machine learning algorithms. The following is a flow chart that illustrates the stages of this research from raw data input to evaluation of prediction results. Shown in Figure 1.

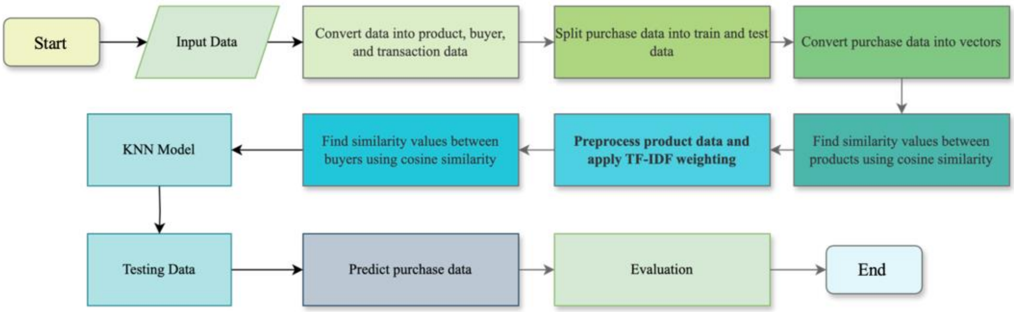

Figure 1. Research methodology

Here is a detailed explanation in paragraph form for each stage:

1. Start: This process begins by marking the beginning of the entire procedure.
2. Data Input: Raw data from purchase transactions is entered into the system. This data includes various important attributes such as IDTransis that uniquely identify each transaction, Transaction Date and TimeTransaction which records when the transaction was made, IDProde and Product Name that identifies the product purchased, Amount that indicates the quantity of the product, Discount given, Payment Method used, Subscriber ID that identifies the customer, AgeCustomer, GenderCustomer, LocationCustomer, Loyalty Points that the customer has, CouponsUsed in transactions, RatingFeedback from customers, and Total Spend that reflect the total value of spending in the transaction.
3. Transform data into product, buyer, and transaction data: At this stage, the raw data that has been collected is broken down into several separate entities. Product data contains detailed information about each product such as Product ID, Product Name, and other attributes. Buyer data contains information about each buyer such as Subscriber ID, Customer's Age, Customer's Gender, and Customer's Location. Transaction data records what products are purchased by each buyer in each

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transaction. At this stage, data that originally combined many products in a single transaction is broken down into a more structured format.

4. Split purchase data into train and test data: Purchase data that has been split is then divided into two parts: training data and test data. This division is carried out in a certain proportion, for example 80% for training data and 20% for test data. The purpose of this division is to ensure that the model to be built can be tested for performance after being trained with training data.
5. Convert purchase data to vectors: Transaction data that has been broken down is converted into vector representations. This involves the formation of a product-buyer matrix where the rows represent the buyer and the columns represent the product, with the values within the matrix indicating whether the buyer bought a particular product and how much. Each buyer and product is represented as a vector within a higher feature space, allowing for further mathematical analysis and the application of machine learning algorithms.
6. Finding the similarity value with cosine similarity: At this stage, the similarity value between the products is calculated using the cosine similarity method. Cosine similarity measures the similarity between two vectors by calculating the cosine of the angle between them. It helps in identifying products that are often purchased together by buyers.
7. KNN Model: The KNN (K-Nearest Neighbors) model is then built using processed data. The model is trained with training data to understand patterns in the data. The K-NN algorithm is used to make predictions based on similarities between buyer vectors, by using the K-values of the nearest neighbor to determine the prediction result.
8. Testing Data: The testing data is used to test the KNN model that has been built. The model is tested with test data to assess its performance. The goal is to examine how well the model can predict the correct outcome based on data that has never been seen before.
9. Prediction of purchase data: The KNN model predicts new purchase data based on test data. The model predicts what products a buyer is likely to buy based on patterns that have been learned from the training data, using similarities between buyer vectors to determine which products are most likely to be purchased.
10. Evaluation: The evaluation stage is conducted to assess the performance of the model. Metrics such as accuracy, precision, recall, and F1-score are used to evaluate the prediction results. The prediction results are compared with actual data to measure how well the model performs predictions, and this evaluation provides insight into the model's strengths and weaknesses.
11. Completed: This stage marks the end of the overall process. The results of the evaluation are used to make further improvements to the model if needed, ensuring that the model is continuously improved to provide more accurate and reliable results.

3. RESULTS AND DISCUSSION

3.1 Analysis

This section discusses the results obtained from the research as well as the analysis and interpretation of existing findings. The latest input data is from 10,000 transaction data made at retail from January to December 2023, and product data of 5302 types of products. A sample of the data is shown in Figure 2.

	IDTransaksi	TanggalTransaksi	WaktuTransaksi	IDProduk
0	4761191	2023-07-31	18:57:04	BDBPK-4273,P-6566,K-8901
1	4761192	2023-03-25	19:49:00	M-7532,BDBPK-0854,P-4906,P-8034,P-0145,P-1099,P-1752,P-...
2	4761193	2023-08-25	14:28:56	P-2132,P-4177,P-1056,P-1517,P-0789
3	4761194	2023-10-27	10:18:19	P-3415,P-1729,P-9632,BBM-1373,P-8478
4	4761195	2023-10-20	10:24:21	P-3401,P-6553,S-5621,BGG-8940,P-3000,P-9077,P-2999,B-67...

Figure 2. Raw data

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From the raw data input, data extraction will be carried out so that it can be broken down into several parts based on each product so that the data becomes 89,908 data as shown in Figure 3.

	IDTransaksi	TanggalTransaksi	WaktuTransaksi	IDProduk	Jumlah	Diskon	MetodePembayaran	IDPelanggan	PoinLoyalit
0	4761191	2023-12-03	16:16:53	PMB-2992	8	11111.1111111111	E-Wallet	SRHJUY-6447002	99
1	4761191	2023-12-03	16:16:53	P-3477	9	11111.1111111111	E-Wallet	SRHJUY-6447002	99
2	4761191	2023-12-03	16:16:53	P-2282	8	11111.1111111111	E-Wallet	SRHJUY-6447002	99
3	4761191	2023-12-03	16:16:53	BDBPK-2493	10	11111.1111111111	E-Wallet	SRHJUY-6447002	99
4	4761191	2023-12-03	16:16:53	P-0177	10	11111.1111111111	E-Wallet	SRHJUY-6447002	99

Figure 3. Transaction breakdown data

This step uses the scikit-learn library in Python, from the results of splitting the data by using the Interaction command on the train data: 390926.6666666667 (79.68%) and Interaction on the test data: 99678.66666666666 (20.32%). Displays information about the user-product matrix, displays the number of features (unique products): 4876. For example, we display the first five products: ['0000' '0002' '0012' '0016' '0017'], then the result is as shown in figure 4.

	0000	0002	0012	0016	0017	0019	0020	0023	0024	0026	0029	0032	0033	0036	0037	0039
SRHJUY-6447000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SRHJUY-6447001	0	0	0	0	0	0	0	0	0	0.087253529	0	0	0	0	0	0
SRHJUY-6447002	0	0	0	0	0	0	0	0	0	0	0	0	0	0.084050319	0	0
SRHJUY-6447003	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SRHJUY-6447004	0.1017943386	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 4. The first five lines of the user-product matrix

Figure 4 displays the first five rows of a user-product matrix, representing the relationship between users and products. Each row, labeled with codes like "SRHJUY-6447000" to "SRHJUY-6447004," corresponds to a unique user within the system. The columns, labeled with numbers such as 0000, 0002, 0012, up to 0039, represent specific products. The values in the table indicate the level of interaction or rating by users for each product. A value of 0 signifies that the user has not interacted with or rated the product, while non-zero values, such as 0.087253529 or 0.084050319, indicate that the user has interacted with or provided a rating or preference for the product. This matrix offers a clear representation of user-product interactions and is typically utilized in recommendation systems to predict products that users might prefer based on their previous behaviors.

	0000	0002	0012	0016	0017	0019	0020	0023	0024
count	1000	1000	1000	1000	1000	1000	1000	1000	1000
mean	0.0020336365	0.0016333185	0.001355434	0.0014161004	0.0022482338	0.0014271753	0.0014121701	0.0020415975	0.0033306701
std	0.014797568	0.0130339025	0.012861569	0.0120516599	0.0155026302	0.0126686061	0.0124706961	0.0146041334	0.0173262765
min	0	0	0	0	0	0	0	0	0
25%	0	0	0	0	0	0	0	0	0
50%	0	0	0	0	0	0	0	0	0
75%	0	0	0	0	0	0	0	0	0
max	0.2050914404	0.1405194602	0.2188048801	0.1265554707	0.1783403836	0.1616308002	0.1523845708	0.162045992	0.1331272132

Figure 5. Matrix Statistics

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In this stage, the purchase data has been converted into a vector representation using TF-IDF (*Term Frequency-Inverse Document Frequency*). The result is a user-product matrix with dimensions of 1000 x 4876, where each row represents a customer and each column represents a product. The values in the matrix show how important a product is to a customer based on the frequency of purchases and the uniqueness of the product among all customers. This matrix has a high level of sparsity (97.95%), which means that most of the values in the matrix are zero. This is a common characteristic in recommendation data, where most customers only buy a small fraction of the total available products. This vector representation allows us to perform further mathematical analysis and apply various machine learning algorithms to the recommendation system.

Furthermore, the KNN algorithm with the Collaborative Filtering, Content-Based, or Hybrid method is run to find top-n recommendations to a buyer. The Collaborative Filtering method uses similarities between buyers as the basis for recommendations. The Content-Based method uses similarities between products as the basis for recommendations. Meanwhile, the Hybrid method combines the results of Collaborative Filtering and Content-Based as the basis for recommendations. The test data from the 5-fold cross-validation process is used as input to make predictions. The results of the prediction are then calculated with precision, recall, and F-measure values to determine the performance of the method used in product personalization.

The KNN model predicts new purchase data based on test data. The model predicts what products shoppers are likely to buy based on patterns learned from training data, using similarities between buyer vectors to determine which products are most likely to be purchased." With data:

'UsiaPelanggan': 20,
'JenisKelaminPelanggan': "F,
'LokasiPelanggan': 'Bukittinggi',
'PoinLoyalitas': 10,
'MetodePembayaran': 'Tunai',
'KuponDigunakan' '1',.

Based on the analysis of the nearest neighbors in the KNN model, here are the recommended products for these new customers:

1. GREEN LEAF CETAKAN AGAR AGAR 0966 DORI
2. AMSAFE BLUE PISAU CUKUR
3. PERASAN JERUK PLASTIK LEMON SQUEEZER
4. NAGATA SIKAT BOTOL 336
5. ENFAGROW A+ 3 PLAIN 400GR

3.2 Recommendations

1. Product Variety: Recommendations cover a wide range of product categories, including kitchenware, personal care, and baby products. This shows that customers with similar profiles have diverse interests.
2. Customer Preferences:
   a. Kitchenware: GREEN LEAF CETAKAN AGAR AGAR 0966 DORI and PERASAN JERUK PLASTIK LEMON SQUEEZER show interest in kitchen appliances.
   b. Personal Care: AMSAFE BLUE PISAU CUKUR Demonstrate interest in personal care products.
   c. Baby Products: ENFAGROW A+ 3 PLAIN 400GR show interest in baby products.
3. Marketing Strategy:
   a. Bundling: Consider creating a product package that combines multiple items from a recommended list, such as a kitchenware package or a personal care package.
   b. Targeted Promotion: Focus your promotion on the product categories that appear in the recommendations, especially kitchen appliances and baby products.
   c. Personalization: Use this information to personalize marketing offers and communications to customers.
4. Improved Customer Experience:

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Given the high rating predictions (5), the main focus should be on maintaining a high level of customer satisfaction:

a. Customer Service: Maintain a high quality of customer service to ensure a satisfying shopping experience.
b. Product Education: Provide detailed information about the benefits and how to use the product, especially for kitchen and baby products.
c. Loyalty Program: Leverage customer loyalty points (10 points) to provide special offers or discounts.

5. Location Analysis:
   The customer is from Bukittinggi. Consider tailoring product recommendations to local preferences or trends in the area.
6. Payment Methods:
   Customers use the Cash payment method. Consider offering incentives if using digital payment methods to improve transaction efficiency.
7. Coupon Usage:
   Customers use coupons (KuponDigunakan: '1'). This shows that customers are responsive to promotions. Consider offering additional coupons or discount programs to increase loyalty and value of shopping.

Taking all these factors into account, the main focus should be on maintaining a high level of customer satisfaction and offering products that match the preferences seen from the recommendations.

3.3 Evaluation

The test was carried out to evaluate the performance of the Collaborative Filtering method, this test was carried out by calculating the precision, recall, and F-measure values of each method. The testing process uses the 5-fold Cross-Validation method, which divides the data into five parts. In each iteration, one part is used as test data and the other four parts are used as training data. This process is repeated five times so that each piece of data is used as test data once. The percentage of data used in this study is 80% for training data and 20% for test data. In this study, there were 10,000 transactions that were processed and extracted into 89,908 transaction data. The test was carried out using k parameters, namely 10, 30, 50, 80, 100.

The following are the results of the evaluation of the KNN model with various k values (10, 30, 50, 80, 100) using the Collaborative Filtering method:

1. k=10: Precision=0.8319, Recall=0.8311, F1-measure=0.8312
2. k=30: Precision=0.5330, Recall=0.5326, F1-measure=0.5325
3. k=50: Precision=0.4437, Recall=0.4437, F1-measure=0.4436
4. k=80: Precision=0.3833, Recall=0.3831, F1-measure=0.3831
5. k=100: Precision=0.3684, Recall=0.3683, F1-measure=0.3683

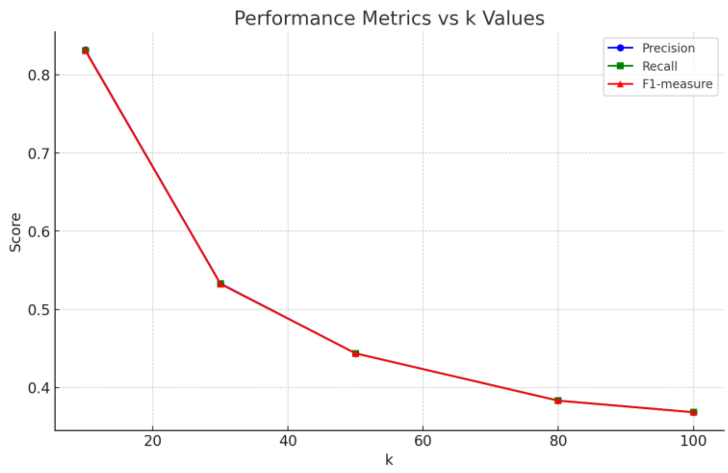

Figure 6. Graph of collaborative filtering evaluation results

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Figure 6 shows a graph of the model's performance based on three main metrics: Precision, Recall, and F1-measure, with variations in k k values. At k = 10 k = 10, Precision reaches 0.8319, Recall 0.8311, and F1-measure 0.8312, indicating optimal model performance. However, when k k increases to k = 30 k = 30, the values decrease to 0.5330 for Precision, 0.5326 for Recall, and 0.5325 for F1-measure. This decline continued as k increased: at k = 50 k=50, Precision, Recall, and F1-measure were all around 0.4437; at k = 80 k=80, all three metrics were around 0.3831; and at k = 100 k=100, Precision dropped to 0.3684, while Recall and F1-measure were both around 0.3683. This decrease in performance indicates that a larger k value causes the model to become less accurate and more susceptible to noise, thus reducing the overall performance of the model.

3.4 Discussion

This study successfully shows that the application of the K-Nearest Neighbor (KNN) algorithm can make a significant contribution in understanding and predicting consumer behavior in the modern retail industry. With a dataset of 10,000 transactions and 5,302 product types, we were able to process the data into 89,908 more structured transaction records for further analysis. The results of the KNN model evaluation using 5-fold cross-validation showed that the value of k = 10 k = 10 produced the best performance with a precision of 0.8319, a recall of 0.8311, and an F1-score of 0.8312. These values indicate that the KNN model is able to provide accurate and consistent predictions in the context of product recommendations. An increase in k value above 10 indicates a decrease in performance, indicating that the model is becoming less accurate and more susceptible to noise in the data. Using the KNN method, we can identify products that consumers are most likely to buy based on previous purchase patterns. For example, the analysis shows that consumers with certain profiles are more likely to buy products such as kitchenware, personal care, and baby products. This information can be used to develop more targeted marketing strategies, such as product bundling and targeted promotions. This research makes several practical contributions to the retail industry, including improving customer satisfaction, effective marketing strategies, and operational optimization. More accurate product recommendations can improve the customer shopping experience, which in turn increases customer satisfaction and loyalty. Information on product preferences can be used to create more effective and targeted marketing campaigns, while the use of AI and big data allows retailers to optimize operations and reduce inefficiencies in inventory management and product offerings. Although this study shows promising results, there are some challenges and limitations that need to be considered. The quality and quantity of data greatly affect the performance of the model; Incomplete or unrepresentative data can reduce the accuracy of predictions. The implementation of the KNN algorithm also requires quite complex data processing and significant computing resources. In addition, models need to be constantly adjusted and updated based on changes in consumer behavior and dynamic market trends. This study provides evidence that the KNN algorithm can be effectively implemented to identify consumer behavior and product personalization in the retail industry. Thus, the use of AI and big data not only increases customer satisfaction but also provides a competitive advantage for retailers in facing the challenges of the digital era.

4. CONCLUSION

This study successfully shows that the use of the K-Nearest Neighbor (KNN) algorithm can effectively identify consumer behavior and provide product personalization in the modern retail industry. Using a dataset of 10,000 transactions and 5,302 product types, we processed the data into 89,908 more structured transaction records and found that a value of k = 10 k = 10 provided optimal performance with a precision of 0.8319, a recall of 0.8311, and an F1-score of 0.8312. These results show that KNN is able to provide accurate and relevant predictions in the context of product recommendations, which in turn can increase customer satisfaction and loyalty. The research also provides important insights for retailers on how to leverage AI and big data to optimize their marketing and operational strategies. However, the study also reveals several challenges, such as the need for quality and representative data, as well as the complexity in data processing and the computing resources required. Therefore, continuous adjustment and update of the model is essential to ensure the accuracy of predictions and relevance to changes in consumer behavior and market trends. Overall, this study

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proves that the application of KNN in big data analysis can provide practical and strategic solutions for the retail industry to remain competitive in the digital era. The use of this technology allows retailers to be more responsive to consumer needs and preferences, as well as improve a more personalized and satisfying shopping experience.

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