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Comparison of KNN and Random Forest Algorithms on E-Commerce Service Chatbot

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Abstract

Technology heavily influences our lives, with the expansion of e-commerce being an important outcome that demands attention. Given the prevalence of smartphones equipped with messaging apps and fast networks, people often utilize these platforms to communicate with sellers, offering a convenient way for sellers to engage efficiently with a diverse customer base. Recognizing this trend, there is a need for digital transformation of services to improve operational efficiency. Thus, this study aimed to compare the efficiency of classification algorithms in e-commerce service chatbots. The researcher used machine learning techniques with KNN and Random Forest algorithms in this case. To assess the feasibility of the application, the chatbot results will be tested using the confusion matrix method to assess accuracy. From this study, it was obtained that the KNN method and calculating word weight using TF-IDF produces an accuracy value of 71.4%, thus confirming its feasibility.

Keywords: Chatbot, E-Commerce, NLP, KNN, Random Forest

Abstrak

Teknologi sangat memengaruhi kehidupan kita, dengan perkembangan *e-commerce* menjadi salah satu hal penting yang patut diperhatikan. Dengan adanya *smartphone* yang dilengkapi aplikasi pesan dan jaringan cepat, orang sering memanfaatkan platform ini untuk berkomunikasi dengan penjual, memberikan cara yang nyaman bagi penjual untuk berinteraksi secara efisien dengan berbagai pelanggan. Menyadari tren ini, diperlukan transformasi digital layanan untuk meningkatkan efisiensi operasional. Oleh karena itu, penelitian ini bertujuan untuk membandingkan efisiensi algoritma klasifikasi dalam chatbot layanan *e-commerce*. Dalam penelitian ini, peneliti menggunakan teknik pembelajaran mesin dengan algoritma KNN dan Random Forest. Untuk menilai kelayakan aplikasi, hasil chatbot akan diuji menggunakan metode *confusion matrix* untuk menilai akurasi. Dari penelitian ini, diperoleh bahwa metode KNN dan perhitungan bobot kata menggunakan TF-IDF menghasilkan nilai akurasi sebesar 71,4%, sehingga mengonfirmasi kelayakannya.

Kata Kunci: Chatbot, *E-Commerce*, NLP, KNN, Random Forest

1. INTRODUCTION

The influence of technology permeates every facet of our lives, and the emergence of e-commerce stands out as a consequential outcome. In today's era, the widespread ownership of smartphones equipped with quick messaging and networking applications has become a norm. Individuals leverage these applications to interact with sellers, offering sellers a convenient means to efficiently respond to a diverse customer base (Rakhra et al., 2021). Introducing a powerful tool in this context, chatbots are gaining prominence in the business sector for their potential to automate client service and streamline human efforts. These conversational agents are pivotal in bridging the gap between human-human and human-computer interaction, demonstrating their capability to comprehend the context and provide appropriate responses (Reddy Karri & Santhosh Kumar, 2020).

Customer service in e-commerce is crucial for assisting site users inquiring about the products and services offered there. However, there are restrictions on customer service, including working hours that are not every time and a lack of responsiveness in answering customers' questions and can impact the efficiency of e-commerce (Astuti & Fatchan, 2019). One may encounter problems when using traditional customer service operated by humans, such as time efficiency, long hold times, conventionality, and errors in the information provided can be easily solved using a chatbot (Wibowo et al., 2020).

Chatbot technology represents a specific application of Natural Language Processing (NLP). NLP, a field within science, delves into the study of communication between humans and computers through natural language (Rosyadi et al., 2020). Various technologies empowered by Artificial Intelligence (AI) include automation, Machine Learning (ML), Natural Language Processing (NLP), machine vision, expert systems, and robotics. Additionally, AI has profoundly influenced diverse facets of life, encompassing healthcare, education, business, finance, manufacturing, and law (Kumar & Ali, 2020).

Machine learning employs programmed algorithms to anticipate output values based on analyzed input data within a suitable range. In this study, a chatbot is developed using supervised techniques rooted in machine learning and natural language processing (Zhang et al., 2020). These supervised techniques involve a mathematical model comprising labeled inputs and anticipated outputs for predictive modeling. Commonly utilized algorithms include Nearest Neighbor, Decision tree, Support vector machines, Naïve Bayes, and linear regression (Tamizharasi et al., 2020). Subsequently, NLP explores computers' ability to comprehend and process human language to generate responses. Various methods are employed to grasp the words and intentions of a user within a given context, ranging from basic searching patterns of texts in user messages to more advanced artificial intelligence techniques applied to the language used by humans (Chandra et al., 2020).

The researchers see several studies that use several algorithms to apply machine learning classification models. In research, A. Wibisono explained that Based on the comparison of trial results, the Random Forest algorithm performance measure has better results than the Naïve Bayes, K-Nearest Neighbor, and Decision Tree algorithms with the k-fold cross-validation method. The Random Forest algorithm can provide an average accuracy result of 85.66% (Wibisono & Fahrurozi, 2019). Furthermore, according to K. Nugraha's research, the built chatbot system can work well and provide a maximum accuracy value of 53.48% (Nugraha & Sebastian, 2021). Tamizharasi, in his research, also shows the accuracy test value of the chatbot system with the accuracy results of KNN at 87.66% and Naïve Bayes at 81% (Tamizharasi et al., 2020).

The present study employs K-Nearest Neighbor (KNN) and Random Forest algorithms because of their proficiency in handling text-based classification problems, which are fundamental to creating an e-commerce service chatbot. The selection of KNN was based on its computational efficiency and simplicity, particularly when categorizing data with a basic distribution. KNN is a non-parametric method that can be used in chatbot systems with little data because it doesn't require assumptions about the data distribution (Jiang et al., 2018). However, when working with big or complicated datasets, KNN suffers from a huge rise in computation time.

Meanwhile, Random Forest offers benefits in terms of accuracy and robustness, particularly for more complicated datasets. Merging several decision trees lowers the possibility of overfitting, which frequently happens in models with just one decision tree (Hoekstra et al., 2022). Because of this benefit, Random Forest is more reliable in making correct predictions, even when the data exhibits significant unpredictability.

In this experimental study, researchers tried to use the K-Nearest Neighbors (KNN) and Random Forest algorithms in machine learning. These algorithms will be used in building an e-commerce service chatbot and tested to get stable results for analysis.

2. METHODS

2.1 Flow Research

The first stage is the literature review stage, where information on previous research related to the research to be used as a reference is sought. The needs analysis stage is conducted to formulate the needs used during the research. The system implementation stage involves integrating machine learning into the chatbot, which includes creating the machine learning, training the data set, and creating a chatting application for testing the chatbot (Intan, 2019). The evaluation stage follows, where the chatbot is checked for successful integration and operation, and the accuracy of the machine learning created in the chatbot is tested (Mohey, 2016). In addition, a model validation step was also conducted to ensure that the chatbot performance was as expected and that the model could be used effectively in practical situations.

2.2 Data Collection

Data collection aims to obtain interactions between the chatbot and the service users. The dataset is collected based on the number of questions in the e-commerce application related to products, orders, shipping, promotions, sellers, returns, and payment services. In this regard, the collection of questions is also based on the top questions that frequently occur and are repeatedly asked by users of the application before and after making transactions on the e-commerce application (Jadhav & Kalita, 2019).

2.3 Natural Language Processing (NLP)

Text processing using the natural language processing (NLP) process is used so that the chatbot can understand the language used by humans (Mathew et al., 2019). NLP tries to understand the language spoken by humans and classifies, analyzes, and responds to text input in the question column. Then, the chatbot tries to analyze the question and adjust it to the dataset. Python has a set of libraries that meet NLP needs. Chatbot data will be extracted from the NLP layer, and the extraction result will respond to the question given to the user (Rakhra et al., 2021).

One of the objectives of successful artificial intelligence is for computers to digest information to the point where they can carry out jobs that people can. Humans frequently exchange information through discussion, which is comparable to the task of asking and answering questions. The question-answering problem can be approached in several ways, including rule-based, extractive, and generative approaches (Rizqullah et al., 2023). The foundation of the rule-based approach is the use of predetermined patterns to elicit answers, based on research on rule-based question answering. Several investigations have used the extraction approach. The questions and answers in the extractive approach are based on a passage or context, and the responses are taken out of the context as answer spans (van Aken et al., 2019). NLP allows the chatbot to classify, analyze, and generate appropriate responses based on the text input. In this study, the following preprocessing techniques were implemented before the classification stage:

a) **Tokenization**: This technique was used to divide the text into smaller chunks, called tokens, like words or sentences. The phrase "What are the shipping options?" for example, is broken down into the tokens "What," "are," "the," "shipping," and "options. " (Baykara & Güngör, 2022).
b) **Stopword Removal**: Using a predetermined stopword list, common words like "and," "in," and "which," which don't significantly aid in the classification process, were eliminated. This

phase enhances the emphasis on important words and helps reduce noise (Zhang et al., 2020).

c) **Stemming and Lemmatization**: Words were reduced to their most basic forms to lessen variance in text representation. For instance, "purchase" was shortened to "buy." Lemmatization uses language norms to guarantee more contextually accurate findings, while stemming offers a heuristic-based method (Yunanto et al., 2023).

d) **Text Representation**: Two methods were used to convert processed text data into numerical representations. The first method uses TF-IDF (Term Frequency-Inverse Document Frequency), which ranks more informative terms by weighing the importance of a document's words about the corpus. Next, the Bag of Words (BOW) is used. Without considering word order, this method displays text as a matrix of word frequencies. During the classification step, these numerical representations allow KNN and Random Forest algorithms to process data efficiently (Li & Zhang, 2023).

e) **Spelling Check**: A spelling correction module was incorporated into the preprocessing pipeline to fix typographical problems. This step guarantees that user searches that contain misspellings are nonetheless appropriately categorized (Wang et al., 2021).

Following preprocessing, a trained NLP model processed the text data to find patterns and forecast query categories. By using TF-IDF or BOW-based representations for this prediction, the chatbot could group inquiries into pre-established classes according to how closely they matched the labeled dataset. Based on these predictions, the chatbot gave pertinent answers (Dogan & Uysal, 2020).

These preprocessing procedures greatly improve the chatbot's capacity to correctly read user input, which raises classification accuracy and improves user satisfaction.

2.4 KNN and Random Forest

KNN and the random forest are very simple and efficient machine-learning algorithms. KNN is very familiar in pattern recognition or design, and this algorithm is widely used where the input sample data and its classes are fixed. This algorithm works if new input data is obtained; it will be classified based on similarity to other data. For example, in asking about promotions that apply to the e-commerce application, data will be classified based on keywords that lead to stored datasets previously. The result is data that is relevant to or close to the question. The random forest is a machine learning algorithm commonly used to combine the output of several decision forests to achieve results to handle classification and regulation problems (Ahmad et al., 2022).

The K-Nearest Neighbor (KNN) algorithm is a machine learning algorithm used to classify new objects based on the distance between test data and training data (Rahardja et al., 2019). ja et al. This algorithm is a non-parametric technique because the classification of test data points depends on the nearest training data point without considering the data point parameters. The accuracy of this algorithm will be higher when it has large enough training data (Sukmandhani et al., 2023). The KNN algorithm uses the equation from the calculation of the Euclidean distance.

In the process of designing the Random Forest algorithm model, the Random Forest algorithm model is built using 'n' Decision Tree trees by finding the best 'n' value, then the optimum results of the Random Forest algorithm, the CART algorithm as a criterion, and using the best splitter to get the best accuracy results in the case of coronary heart disease data (Singh et al., 2023).

2.5 Evaluation

Evaluating the Confusion Matrix is a method used to evaluate the classification results of a model. The Confusion Matrix is a table representing the number of correct and incorrect predictions made by a model. The Confusion Matrix consists of four parts: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) (Wijanarko & Afrianto, 2020).

a) True Positive (TP) is the number of correct predictions from the positive class. This indicates that the model has successfully and correctly classified the positive class.
b) False Positive (FP) is the number of incorrect predictions from the negative class. This indicates that the model has wrongly classified the negative class as positive.
c) True Negative (TN) is the number of correct predictions from the negative class. This indicates that the model has successfully classified the negative class correctly.
d) False Negative (FN) is the number of incorrect predictions from the positive class. This indicates that the model has wrongly classified the positive class as negative.

From these four parts, the success rate of a model in classifying data can be seen. The higher the values of TP and TN, the better the model is at classifying the data. On the other hand, the higher the values of FP and FN, the worse the model is in classifying the data. Evaluating the Confusion Matrix is very important because it can provide accurate information about the success rate of a model in classifying data. In addition, the Confusion Matrix can also be used to calculate metrics such as accuracy, sensitivity, and specificity, which can help evaluate a model's performance (Bird et al., 2023).

Accuracy is the success rate of a model in classifying data overall, calculated by adding TP and TN and dividing by the total number of data tested. Evaluating the Confusion Matrix is very useful in evaluating the performance of a model, especially for imbalanced data. Imbalanced data is data where the number of positive and negative classes is not balanced, which can cause the model to be too sensitive or specific. By using the Confusion Matrix, the accuracy, sensitivity, and specificity of a model can be known, allowing for improvement if necessary (Fachreza et al., 2023).

3. RESULTS AND DISCUSSION

3.1 Chatbot Concepts

In creating a chatbot, we apply several algorithms and frameworks that help optimize the use of chatbots. In this case, we create a scheme that can help process data so that it can be displayed in the form of a chatbot. We show it in Figure 1, which explains the chatbot's flow, starting from the user inputting data. The data will be processed using NLP, where the system will predict and provide answer recommendations based on the questions given by the user. After the data is processed, there is a spelling check so that the input words are correct, and then the data will be checked in the system database. If the question is in the database, the answer displayed is appropriate, but if the answer is wrong, it will provide a default answer from the system.

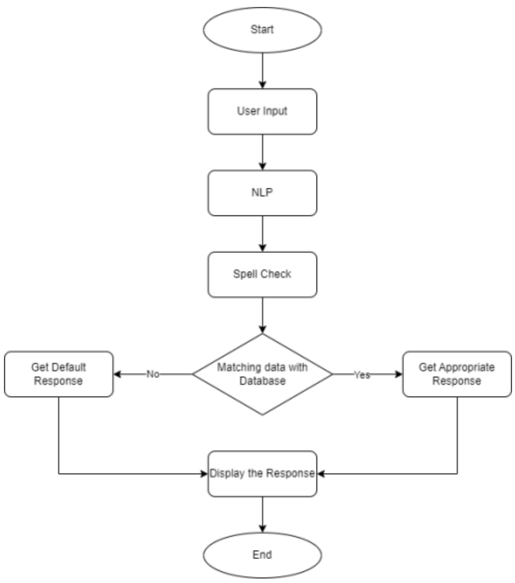

Figure 1 Chatbot Flowchart

3.2 Dataset Collection

The data collection stage is carried out by collecting Frequently Asked Question (FAQ) chat data from several e-commerce tools that can help customers. In addition, data is also collected through observations related to e-commerce to several places and people who have a relationship in the buying and selling process. From this stage, 300 question data were collected, which will be used for the following process.

The collected data is stored in a text file in JSON (JavaScript Object Notation) format as a knowledge database. The file structure consists of the 'knowledge' attribute, which contains classes resulting from the grouping of all the data that has been collected. Each class has a 'class' attribute to store the class name, 'patterns' to store a list of questions related to the class, and 'responses' contains a list of answers related to the class. The following dataset class distribution will be shown in Table 1.

Table 1 Database Class

Class	Description	Data
Description	Questions related to store description and information	50
Delivery	Questions related to store delivery service	50
Payment	Questions related to store types and method	50
Promo	Questions related to promos provided by the store	50
Return	Questions related to return service	50
Product Recommendation	Questions related to product recommendations from the store	50
	Total Data	**300**

3.3 Data Pre-processing

Preprocessing is a crucial step in Natural Language Processing (NLP) that guarantees machine learning models can understand the text. Tokenization, the first step in the preprocessing process in this study, divides the text into units of words called tokens. After that, frequent terms like "and," "in," and "which" that don't add anything to the classification are eliminated through the process of stopword removal. After that, words are reduced to their most basic form via stemming or lemmatization, for example, "purchase" becoming "buy”. The TF-IDF and Bag of Words (BOW) approaches represent the text in numerical form; this step is crucial to enabling the KNN and Random Forest algorithms to process the text efficiently.

Following the completion of preprocessing, an NLP model is trained to identify patterns in the text and process the processed text. Based on the degree of similarity with the available dataset, these models predict the question's class using TF-IDF or BOW-based text representations. The chatbot responds appropriately based on these predictions. Additionally, the chatbot has a spelling check function that can handle typos in user input to increase accuracy.

3.4 Classification Model

The KNN approach for class construction creates a model based on a pre-specified number of k nearest neighbors. KNN uses the Euclidean distance to determine how far new data is from the remaining training data whenever it is received. When new data needs to be classified, this method computes the distance immediately rather than requiring explicit model training. In the meantime, several decision trees are created in Random Forest to build the model. Bootstrap sampling trains each tree with a random subset of the dataset. Each tree's construction features are likewise chosen at random. Different decision trees are produced by this method, which lessens overfitting and increases the stability of the model.

The KNN algorithm then uses the k nearest neighbors of the newly received data to make predictions for its prediction model. The final prediction will be determined by looking at the class that shows up the most among those neighbors. In contrast, every decision tree in the Random Forest makes a forecast on brand-new data. The majority votes on every decision tree to establish the final prediction. Compared to employing a single tree, this method guarantees stronger and more stable predictions.

3.5 Chatbot Display

This chatbot application is intended to help the efficiency and effectiveness of services in e-commerce, so the features and appearance are made according to needs. The results of the chatbot display will be shown in Figure 2.

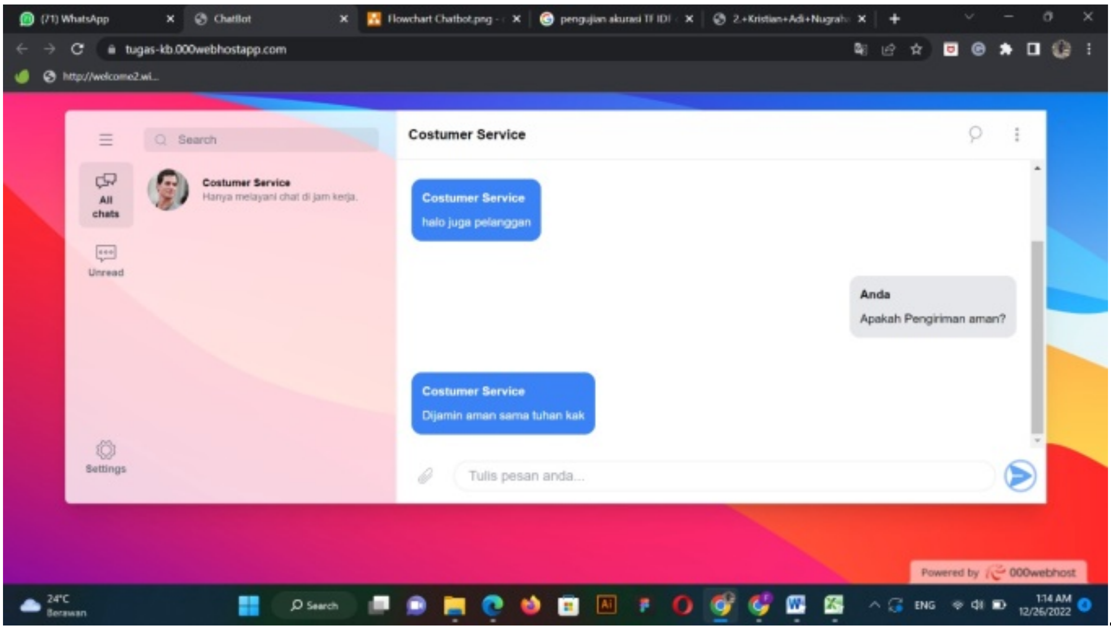

Figure 2 Chatbot Display

The chatbot display contains chats that have been sent and answers from the system occupying the right column, and the left contains the history of chats that have been sent. The display is made simple so that users can easily understand it. There is a settings menu at the bottom left. Besides that, users can also search for chat history on the lup icon on the top right.

3.6 Accuracy Testing

Bot accuracy testing is carried out to determine the level of response accuracy the bot gives when users search using the bot application. This test is done by sending text messages directly to the bot. The test dataset used in this study is 70 pieces, and the following formula will obtain the accuracy value. Accuracy testing is conducted to assess how well the KNN and Random Forest models classify user queries. The models were tested using two text representations: TF-IDF and Bag of Words (BOW). In this test, there are several different test methods. The following results of the accuracy test will be displayed in Table 2.

$$Accuracy = \frac{Number\ of\ Correct\ Answers}{Total\ number\ of\ answers} \times 100\% \tag{1}$$

Different accuracy results are obtained for each method, and the test is used based on the test results. Using the KNN method and calculating word weight using TF-IDF produces an accuracy value of 71.4%. Then, the use of KNN and BOW methods yielded an accuracy of 52.8%. Using

Random Forest and calculating word weights using TF-IDF produces an accuracy value of 61.4%. Moreover, finally, testing using Random forest and BOW has an accuracy value of 57.1%.

Table 2 Accuracy Testing

Testing	Correct Answer	Accuracy
KNN & TF-IDF	50	71,4%
KNN & BOW	37	52,7%
Random Forest & TF-IDF	43	61,4%
Random Forest & BOW	40	57,1%

4. CONCLUSIONS

KNN and Random Forest algorithms to solve the e-commerce service chatbot problem. This research uses a dataset that we compiled and collected from various e-commerce with 300 questions. The measurements made by machine learning algorithms show the best accuracy and classification model. The highest accuracy value was obtained using the KNN method, and word weight calculation using TF-IDF resulted in an accuracy value of 71.4%, while testing using random forest and BOW yielded an accuracy value of 57.1%. This proves that the KNN Method and the calculation of word weights using TF-IDF are better at word processing.

Compared to previous studies, Tamizharasi et al. (2020) reported an accuracy of 87.66% using KNN with TF-IDF in the context of a medical chatbot. Although this study's accuracy is lower at 71.4%, the difference can be attributed to the domain-specific nature of datasets (e-commerce vs. medical) and the relatively smaller dataset used in this research. Furthermore, Nugraha & Sebastian (2021) achieved only 53.48% accuracy for a KNN-based chatbot, underscoring the effectiveness of the preprocessing and text representation methods applied in this study. These findings suggest that the KNN algorithm with TF-IDF is a promising approach for text-based classification in chatbot systems, particularly in domains with smaller datasets. However, the relatively lower performance of Random Forest in this study indicates that further exploration of hyperparameter tuning or feature engineering could improve its effectiveness.

This research contributes to the growing body of knowledge on e-commerce chatbot systems by demonstrating the effectiveness of KNN with TF-IDF for handling text classification tasks. For future research, the researcher recommends expanding the dataset to include more diverse and larger-scale e-commerce queries to improve generalization. The algorithms can use deep learning or neural networks to get maximum results. With these directions in mind, future research can build on the findings of this study to further improve the performance and applicability of chatbot systems in e-commerce.

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