Sentiment Analysis of Customers' Review on Delivery Service Provider on Twitter Using Naive Bayes Classification

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ABSTRACT

Customer evaluations on social media may help us remain competitive and comprehend our business's target market. By analysing consumer evaluations, a business owner can identify common themes, pain points, and desired features or enhancements. By analysing customer feedback across multiple channels, such as social media, online reviews, and customer service interactions, businesses can rapidly identify any negative sentiment or potential brand damage. The contribution of our study is to evaluate the performance of the Naive Bayes method for classifying customer feedback on courier delivery services obtained via Twitter. The Naive Bayes algorithm is selected due to its simplicity, which facilitates efficient computation, suitability for large datasets, outstanding performance on text classification, and ability to manage high-dimensional data. In this investigation, the Naive Bayes classifier accuracy is 0.506, which is considered to be low. According to our findings, the irrelevant feature classification resulting in an error throughout the categorization process. A large number of data appearance characteristics that do not correspond to the testing data category have been identified as a result of this occurrence.

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1. INTRODUCTION

Transportation and distribution of products, parcels, or items from one location to another constitute delivery services. Typically, courier companies, logistics firms, or retailers provide these services to ensure the safe and timely dispatch of products to customers or designated recipients [1], [2].

Delivery services can include a variety of activities, such as:

1. Online shopping deliveries.
   Many online retailers offer delivery services to dispatch products directly to customers' residences or offices. With the growth of online purchasing, this has become increasingly common.
2. Food deliveries
   Restaurants, cafes, and other food establishments frequently offer delivery services to transport customers' meals or food orders to their front entrances. These services may be provided either by the restaurant or by third-party delivery platforms.
3. National postal services
   They deliver letters, packages, and other mail items to both residential and commercial addresses on a large scale. Some delivery services specialise in imperative or time-sensitive deliveries and offer same-day or express delivery options. They prioritise quickness and ensure that shipments arrive at their destinations quickly.

4. Freight and logistics
   Businesses that transport large quantities of products or heavy cargo may provide delivery services for commercial purposes. They manage the transportation, storage, and distribution of goods using a variety of vehicles, including lorries, ships, and aeroplanes.

Delivery services have become indispensable in modern society, providing consumers and businesses with convenience and accessibility. They frequently employ monitoring systems and provide real-time updates to keep customers abreast of the status and location of their deliveries [3]. Speed, cost, and accessibility can vary among delivery services. Some offer same-day or next-day delivery, while others, depending on distance and delivery network, may take longer. Weight, size, and distance of the parcel, as well as any additional services requested, such as insurance or expedited shipping, can affect the delivery fee. Moreover, in order to remain competitive and comprehend the expectations and preferences of the business's target customer, we may investigate social media customer evaluations [3]-[7]. A business proprietor can identify common themes, pain points, and desired features or enhancements by analysing customers' reviews [6]-[9]. This comprehension facilitates a more effective alignment of business offerings with customer expectations, ensuring that products and services meet or transcend customers' needs and preferences.

1.1. Sentiment Analysis

Sentiment analysis is a technology that helps get information from big sets of documents. It lets businesses figure out whether customer feedback is generally positive, negative, or neutral [10], [11]. By analysing sentiment, businesses can gain insight into customer satisfaction, identify areas for improvement [11], [12], and comprehend how consumers view their products, services, or brand [13], [14]. Sentiment analysis may assist in identifying particular issues or problem points that consumers may be experiencing. By analysing negative sentiment, businesses can identify areas in which they need to make improvements. This feedback can be utilised to make strategic decisions, improve product features, resolve customer concerns, and ultimately enhance the customer experience [15], [16].

Sentiment analysis can provide invaluable insights for product development and innovation. By analysing consumer feedback, businesses can identify trends, determine unmet needs, and gather ideas for new features or improvements [17]. This information can be used to guide the development of new products or enhancements to existing ones, ensuring that they meet customer expectations [18] and preferences [19]. Sentiment analysis can quantify the satisfaction of customers [12], [17]. By analysing the sentiment of customer feedback, businesses can assess the effectiveness of customer service initiatives and compare sentiment across products or services [20]. This data assists businesses in measuring customer loyalty [21], identifying areas where they excel, and focusing efforts to increase customer satisfaction. Moreover, sentiment analysis enables companies to monitor and assess their brand reputation in real-time [22]. By assessing customer feedback across multiple channels, including social media, online reviews, and customer support interactions, businesses can quickly identify any negative sentiment or potential brand damage. This allows them to respond immediately and take the necessary steps to mitigate negative sentiment and preserve their brand reputation [22]-[24].

Twitter's user base consists of millions of active users [25]. Consequently, obtaining consumer feedback via Twitter can be advantageous. This makes it a useful resource for gathering diverse consumer feedback and opinions. Businesses can access a diverse and representative sample of their customer base and gain a deeper understanding of customer sentiment by mining Twitter for customer sentiment. Twitter provides a forum for users to communicate their real-time opinions and experiences [26]. By monitoring Twitter conversations, businesses can collect rapid consumer feedback and gain insight into how customers feel about their products, services, or brand [27], [28]. This allows for prompt responses and proactive actions to alleviate problems or capitalise on positive emotions. Moreover, Twitter is a public forum in which users freely convey their thoughts and opinions [29]. Therefore, it is an excellent source for conducting sentiment analysis. By extracting consumer opinions from Twitter, businesses can analyse the sentiment associated with their brand, products, or services on a large scale [30], [31]. This analysis assists in determining the overall perception of the brand by identifying any positive or negative sentiment trends.

Some research [29], [31], [32]-[36] collect data from social media and do an experiment on sentiment analysis. A research by Fitri *et al.* [37] used the Naive Bayes, Decision Tree, and Random Forest algorithms to categorise the tweets. They showed that the accuracy of the Naive Bayes algorithm was superior to that of the Decision Tree and Random Forest algorithms. As part of their study of tweets, Qorib *et al.* [38] combine three vectorization approaches (Doc2Vec, CountVectorizer, and TF-IDF) with five different learning algorithms (Random Forest, Logistics Regression, Decision Tree, LinearSVC, and Naive Bayes). They claimed that LinearSVC with TF-IDF vectorization exhibits the best Twitter sentiment analysis performance. Neogi et al [39] analysed twitter data using Decision Trees, Random Forests, Naive Bayes, and Support Vector Machines. They discovered that Random Forest provided the most accurate classifier.

The contribution of our study is to analyse the performance of Naive Bayes method to classify the customers' feedback that is obtained from the Twitter platform. Moreover, in this study we performed k-fold cross validation when evaluating the model to avoid bias. Naive Bayes algorithm is selected due to its simplicity that allows for efficient computation [40], [41], making it suitable for large datasets [42], [43], good performance on text classification [44], and its ability to handle high-dimensional data [43], [45]. The tools that is used to analyse the massive documents is Rapid Miner. This tool is a popular data science platform that offers a range of features and functionalities for analyzing large datasets. RapidMiner is designed to handle large datasets and can scale to process and analyze massive amounts of data efficiently. It leverages distributed computing and parallel processing techniques [46], allowing users to leverage the power of multiple machines or clusters to analyze data in a distributed manner. This scalability makes RapidMiner suitable for analyzing large-scale datasets that may be challenging to handle with traditional data analysis tools.

2. METHODS

2.1. Data Collection

Twitter jntexpressid was crawled in order to acquire the data needed for this investigation. The data came from customer feedback on the relocation services provided by J&T, such as reviews and comments. For the purpose of this study, the researchers collected data from Twitter over the duration of one month, over the span of March 2022 to April 2022. The data pulled from Twitter were put into positive or negative categories. The tweet's body comprises terms with a positive connotation, which provide support for its meaning, as well as affirmations of agreement, which indicate positive class. A class is said to be negative if the data associated with it contains negative phrases, mocking, and cons. In this research, we also select customer evaluations that were written in proper Indonesian.

2.2. Naive Bayes Classifier

The Naive Bayes classifier is a typical probabilistic machine learning method used for classification applications due to its simplicity and effectiveness. It is based on Bayes' theorem and makes the "naive" assumption that characteristics are independent given the class label [47]. This assumption usually remains true enough in reality to be useful.

There are two phase of Naive Bayes classification namely [48]:

1. Phase of Training:
   - The classifier counts the occurrences of each class in the training data to determine the prior probability of each class label. The training data consists of features (attributes) and class labels.
   - It also calculates the probabilities of feature values given each class label, or likelihood. To do this, we count how often each feature value appears in the training data and then calculate its conditional probability for each class.
2. Phase of Prediction:
   - When presented with an unlabeled instance, the classifier determines the posterior probability of each class label based on the observed feature values.
   - By multiplying the prior probability of the class label by the likelihood probabilities of the observed feature values for that class, Bayes' theorem determines the posterior probability.
   - The instance is categorized into the category with the greatest posterior probability. This is known as the maximum a posteriori (MAP) decision rule.

Advantages of Naive Bayes classifier [49]:

1. Naive Bayes's simplicity makes it a viable option for use in practice. It is effective for huge datasets because of its cheap processing cost.
2. Its performance is consistent even with a large number of features, and it scales well to high-dimensional datasets.
3. Since Naive Bayes simply needs to do elementary probability calculations to produce predictions, once the model is trained, it can do so rapidly.
4. As a result of the independence assumption, the inclusion of irrelevant characteristics has little to no effect on the model's performance.

Limitations of Naive Bayes Classifier [50]:
1. Independence Assumption: The classifier assumes that features are conditionally independent given the class label, which might not hold true in all cases. This can lead to suboptimal performance if the independence assumption is violated.
2. Data Scarcity: Naive Bayes may suffer from the "zero probability" issue if a particular feature value does not appear in the training data for a specific class. This can be mitigated using techniques like Laplace smoothing.
3. Sensitivity to Feature Correlations: Since Naive Bayes assumes independence between features, it may struggle to capture complex relationships or correlations among features.

The following are the steps of the Naive Bayes algorithm:
1. Calculating the prior probability of each class.

$$P(K) = \frac{Nj}{N} \tag{1}$$

Where Nj is number of a document in a class, N is total documents. Divide the number of documents in a class (Nj) by the total number of documents (N) to get the Prior probability.

2. Calculating the likelihood

$$P(x|K) \;=\; P\;(x1, x2, \dots, xn|K) \tag{2}$$

Where K is class, x is attribute vector n, $P(x|K)$ is proportion of documents from class H containing the attribute value x.

The likelihood value is an easy way to predict the spread of data that is often used because it only takes into account the mean and standard deviation of the training data. The feature's likelihood value will be represented using a Gaussian Naive Bayes model. The Naive Bayes Gaussian equation is shown below.

$$P(X_a = x_a|K = k) \;= \frac{1}{\sqrt{2\pi\sigma_k^2}} e^{-\frac{(xa-\mu_k)^2}{2\sigma_k^2}} \tag{3}$$

Where P is probability, Xa is the a attribute, a is value of the a-th attribute, K is certain class, k is sub-class to search, μ is mean shows the average of all features, σ is standard deviation or variance value of all attributes.

3. Calculate the probability of the posterior end

In Bayesian statistics, posterior probability is the revised or amended probability of an event occurring in light of new information. Using the Naive Bayesian equation, the posterior probabilities for each class are computed. After calculating the prior $P(K)$ value, the posterior value is calculated by multiplying the prior $P(K)$ results by the likelihood $P(X|K)$.

$$P(K|X) \;= P(K) * P(X|K) \tag{4}$$

Where K is class that is used as a hypothesis, X is data whose class is not known, $P(K|X)$ is probability of the sample entering into class K (posterior), $P(X|K)$ is the probability of a feature appearing based on the conditions in the hypothesis (likelihood), $P(K)$ is probability of the hypothesis K (prior probability).

4. Find the maximum value of the posterior probability multiplication

Feature classification is determined by selecting the highest class value. The posterior value is then compared with the posterior class results to ascertain the classification class of a feature. The predicted class is the one with the greatest posterior probability.

$$V_{nb} = arg\ max_{vj\in v} P(K)\Pi P(X|K) \tag{5}$$

2.3. K-Fold Cross Validation

K-fold cross-validation is a common resampling technique used in machine learning to evaluate the performance and generalization capability of a predictive model. It assists in estimating the model's performance on unknown data. Cross-validation provides a number of benefits when evaluating and comparing machine learning models [51]:

1. K-fold cross-validation gives a more accurate measure of a model's performance than a simple train-test split. By redoing the training and review process on different parts of the data, the effect of data variation can be reduced, and a more accurate performance measure can be found.
2. Using the information that is available, K-fold cross-validation makes good use of the data that is provided. All of the samples in the collection are used to both train and test the model. This is especially helpful when the dataset is small because it gets the most information out of the data that is there.
3. K-fold cross-validation allows to compare different models or sets of parameters in a fair way. By putting each model through the same review process, the results can be compared with certainty. This helps choose the best model or figure out the best way to set the hyperparameters.
4. K-fold cross-validation helps to reduce the bias that can happen when a certain train-test split is used. By adding up the success measures from different sections, we can get a more accurate and complete picture of how well the model works.

Overall, k-fold cross-validation is a useful method that gives a more accurate idea of how well a model works, allows fair comparisons of models, makes it easier to optimise hyperparameters, and helps find possible problems. It is often used in study and practise in machine learning to measure how well models work and how well they can generalise. In our research, k-fold cross validation was utilized to evaluate the model. k-fold cross validation is the process of dividing data into k equal-sized data sets. Throughout the k iterations, one fold is selected as the test data, while the remaining k folds serve as training data. The value of k can be written as K-1 (2,3,4,5,6,..., n). Consider 5-fold cross validation, which consists of five data subgroups, four of which serve as training data and one as test data. There will be n iterations of training and testing to produce numerous models. Using the mean, the accuracy of the data is then determined by combining the results of each K model.

3. RESULTS AND DISCUSSION

Building a model in RapidMiner provides a comprehensive set of tools and functionalities for data exploration, preprocessing, model selection, evaluation, interpretation, and deployment. It simplifies and accelerates the end-to-end data science workflow, enabling efficient and effective model building for various data analysis tasks. This automation streamlines the process of model building and evaluation, making it easier to reproduce results and iterate on different experiments. Fig. 1 shows the model that is used in this research.

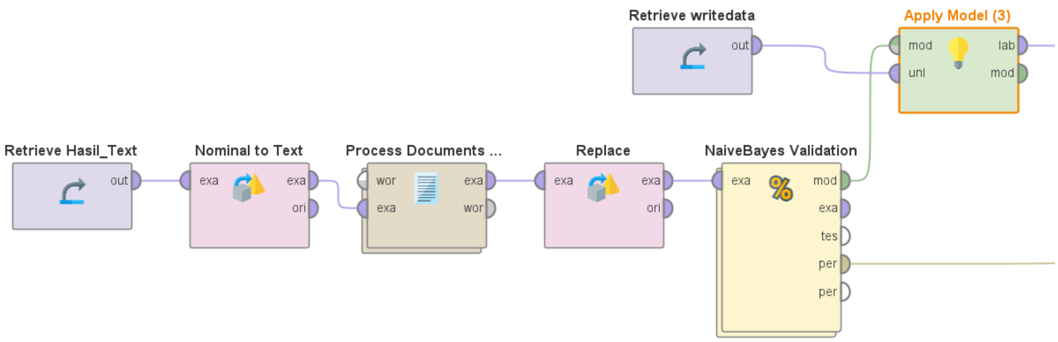

Fig. 1. Rapid Miner model for text classification using Naive Bayes classifier

A word cloud is a method for displaying the most prevalent words in a corpus of text. Larger words indicate increased frequency [52]. Using word clouds, one can assess customer sentiment. Word clouds offer a visual representation of textual data, allowing for a speedier comprehension of the main themes and feelings expressed by consumers. By displaying words in various sizes and colours, word clouds offer an intuitive way to identify the most prevalent and influential terms in customer feedback or reviews. Word clouds offer a concise summary of consumer sentiment, allowing businesses to gain a fast overview of the overall sentiment without analysing each individual comment or review. Fig. 2 depicts a word cloud representation of the data collected for this investigation.

Word clouds provide a high-level representation of sentiment patterns, which can be particularly useful when dealing with large quantities of consumer feedback. It is critical to note that word clouds alone do not offer thorough sentiment analysis or capture the whole context of consumer comments. They should be used in conjunction with other techniques and methodologies for a more comprehensive analysis of consumer sentiment [53].

Fig. 2. Word cloud visualization

In our study, 5-fold cross validation was employed to analyse the model. This validation helps mitigate bias that can arise from the dependency on a particular train-test split. By averaging the performance metrics obtained from multiple splits, it provides a more balanced and representative assessment of the model's performance. Fig. 3 shows the accuracy and F-1 score of 5-fold cross validation in this study.

```
avg_acc [0.5177305  0.54285714 0.45       0.49285714 0.52857143]
Akurasi AVG: 0.506403242147923
avg_pre [0.5890457  0.59345392 0.56202652 0.5375     0.56980656]
Presisi AVG : 0.5703665386492255
avg_rec [0.59432843 0.60544218 0.57753773 0.55899705 0.58565531]
Recall AVG: 0.5843921407757754
avg_scor [0.51712329 0.53947368 0.44521641 0.46302199 0.51875    ]
F1-Score AVG: 0.4967170731162268
```

Fig. 3. The result of 5-fold cross validation

The accuracy of Naive Bayes classifier that is used in this study is 0.506, which is considered low. Itoo *et al.* [54] reported that the Naive Bayes classifier can exhibit lower accuracy compared to more complex machine learning models due to irrelevance features. Naive Bayes is known to be robust to irrelevant features since it calculates probabilities based on the presence or absence of feature values. However, if there are highly irrelevant features that do not provide useful discriminatory information, they may introduce noise into the model and decrease its accuracy. Feki-Sahnoun *et al.* [55] suggested that Naive Bayes is a relatively simple and linear classifier, therefore its expressiveness is limited. Naive Bayes may not be able to capture complex decision boundaries or non-linear relationships between features and class labels. If the underlying data distribution exhibits intricate patterns that cannot be represented well by Naive Bayes, its accuracy may be limited.

From our observation, the dataset classification is erroneous, which has led to an error in the categorization process. Because of this circumstance, a large number of data appearance aspects have been discovered that do not correspond to the category in the data that was utilized for testing. For instance, one of the words that can be found in the positive data class is "fast," as in the phrase "fast delivery service." On the other hand, the data class that contains negative information also contains the word "fast," which is derived from the phrase "not fast enough." Errors in the process of categorization are brought on by the presence of the word "fast" in both positive and negative dataset classes. Therefore, inconsistent categorization of data, as exemplified by the presence of the word "fast" in both positive and negative classes, undermines the reliability of the results. It is crucial to ensure accurate categorization to avoid introducing noise into the model and to provide reliable insights. Further refinement of the categorization process and careful feature selection could help address this issue. Hairani *et al.* [56] stated that Naive Bayes is known to be robust to irrelevant features since it calculates probabilities based on the presence or absence of feature values. However, if there are highly irrelevant features that do not provide useful discriminatory information, they may introduce noise into the model and decrease its accuracy.

4. CONCLUSION

Opinions, comments, evaluations, remarks, and complaints on Twitter are examples of data types that are regarded as massive and therefore cannot be exploited directly. This type of analysis has the potential to increase a company's overall productivity. In this study, we examined the Naive Bayes classifier as a method for categorising consumer opinions regarding the services offered by courier firms. The outcome indicates that the accuracy is deemed low. This issue arose as a result of the fact that some significant terms were classified as both positive and negative due to sentence variation. As a result of this, there is room for further investigation in the field of sentiment analysis to investigate the possibility of applying such a strategy in order to enhance the accuracy of the Naive Bayes classifier.

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