Sentiment Analysis on Marketplace in Indonesia using Support Vector Machine and Naïve Bayes Method

Muhammad Mujahid Dakwah[1], Asno Azzawagama Firdaus[2], Furizal[2], Rangga Alif Faresta[3]
[1]Department of Management, Universitas Mataram, Mataram, Indonesia
[2]Department of Informatics, Universitas Ahmad Dahlan, Yogyakarta, Indonesia
[3]Department of Digital Learning, Monash University, Clayton Victoria, Australia

ARTICLE INFO

Article history:

Received December 25, 2023
Revised February 11, 2024
Published February 20, 2024

Keywords:

Marketplace;
Naïve Bayes;
Sentiment Analysis;
Support Vector Machine

ABSTRACT

This research addresses the challenges of marketplace customer feedback, which is an important aspect in today's era of online transactions. Marketplaces often receive many unsatisfactory comments from their customers through social media platforms. One approach that can be used to address this is sentiment analysis. This research contributes new insights as recommendations for marketplaces based on customer opinions on available services and delivery. The sentiment analysis methods used are Naive Bayes and Support Vector Machine because they are considered the best methods in training text-based classification models. Before being classified, the data goes through preprocessing stages such as cleaning, case folding, filtering, stemming, and tokenizing, as well as feature extraction stages using Term Frequency - Inverse Document Frequency (TF-IDF). The objects analyzed are divided into several well-known marketplaces in Indonesia such as Tokopedia, Lazada, and Shopee in discussing services and delivery of goods. The data used in this study comes from Twitter (X) social media accessed on August 27, 2023, using crawling techniques and successfully obtained as much as 2057 Tweet data. The best accuracy is obtained in the SVM method when compared to the Naive Bayes method. Words obtained based on service talks include price, service, application service, feedback, independence, and others. As for the delivery of goods, common words such as COD, delivery, package, courier, cheap, price, and others appear. Both methods used have good accuracy and can be recommended for use in similar research.

Corresponding Author:

Muhammad Mujahid Dakwah, Department of Management, Universitas Mataram, Mataram, Indonesia
Email: mujahid.fe@unram.ac.id

1. INTRODUCTION

The rapid development of marketplaces on e-commerce platforms makes consumers interested in resale options and marketplace business models [1]. Electronic platforms earn commissions from sales proceeds and suppliers can sell their products directly to consumers through the platform [2]. Because the simple payment model makes consumers increasingly turn to e-commerce. These online shopping payments are almost completely cashless, namely bank transfers (29%), electronic money (25%), and credit cards (20%) [3].

There are three types of agents, namely consumer, online retail, and marketplace [4]. Among these three types of agents, online retail and marketplaces have grown rapidly in recent decades [5]. Marketplace is a digital platform that provides buyers and sellers [6]. One study revealed that marketplaces are critical to lifting millions of small businesses out of poverty [7]. Data marketplaces are intended in other business models for producers to be able to provide offers to different consumers in parallel [8]. Marketplace provides pricing from consumers and operators earn costs through sales proceeds [9]. Research conducted in various settings around the world shows that such marketplaces are highly personal, social, and relational environments, where people and relationships are increasingly important [10],[11]. However, this is also limited because the trust management model of the distribution of goods that does not have the authority to regulate all transactions [12] is seen as a weakness. This reduces customer trust reduced in the marketplace. Starting from products, and prices, to shipping provided by the marketplace to customers.

Social media has a highly significant impact on its users [13]. Social media has grown rapidly and become the most extensive information disseminator in the world in recent years [14],[15]. Twitter (X) is one of the favorite social media platforms because it allows users to send short messages, images, and videos [16]. Twitter (X) users can express their opinions through it [17]. Therefore, many things can be analyzed through this platform. One of them is generating predictions in Twitter data analysis, which has attracted a lot of attention in recent years [18].

Based on this, an approach model is needed that is able to get feedback on respondent's assessments. The feedback model will be useful for policymakers at the marketplace level. Customized policies based on feedback from marketplace users on social media talks. The approach model taken as consumer feedback to marketplace shipping is automatically sentiment analysis. Sentiment analysis has an important role as a measuring tool for the evaluation of existing marketplaces based on feedback from users as marketplace consumers. Sentiment analysis is a computational investigation that can identify emotions, feelings, and viewpoints from textual content [19]. Sentiment analysis is a technology capable of finding feedback [20],[21] in the form of data classifications that focus on positive, negative, or neutral polarity [22]. Sentiment analysis can use classification methods as machine learning models. Many methods can be used, but Support Vector Machine (SVM) and Naive Bayes were selected in this study. SVM was chosen because it is superior to other methods in the sentiment analysis approach [23], for example for some studies [24],[25]. The Naive Bayes method was chosen because it has been applied to several studies [26],[27] and has a higher level of accuracy in the sentiment analysis approach [28]. In addition, sentiment analysis allows the model to obtain customer opinions through online mediums such as surveys, websites, and social media [29]. The platform used in this research to gather customer opinions is Twitter (X). Customer opinion data about the services or delivery of the marketplace platform can be used as valuable information.

Sentiment analysis is not only limited to the discussion discussed earlier, other uses are used as a measure of emotions in marketplace products and have developed [30],[31]. Recent studies apply sentiment analysis to textual data to assess sentiment and the marketplace as a whole [32]. Table 1 describes some of the research related to sentiment analysis, especially on the topic of marketplaces. It describes the data sources used to the methods used in sentiment analysis.

Table 1. Research about marketplace

Refs	Topic	Dataset Used	Classification Method
[33]	Negation in Sentence	Kaggle	Naïve Bayes, SVM, ANN, RNN
[34]	Market Value of AI and ML	Google API Services	Naïve Bayes, Decision Tree, Random Forest
[35]	Indonesian Hotel Review	Traveloka Website	LSTM
[36]	Subsistence Marketplace	Respondents' Data in Bangladesh	Common Method Variance (CMV)
[37]	Mature Destination	TripAdvisor, St. Mark Square, and the Doge's Palace	LSTM
[38]	Indonesian-Based Aspect Sentiment	Indonesian Marketplace	Graph Convolutional Network, Graph Recurrent Network, CNN, RNN, Aspect-Based Sentiment Analysis
[39]	Indonesian Hotel Review	Indonesian Hotel Review	LSTM + attention mechanism
[40]	Indonesian Aspect-Based Sentiment Analysis	Twitter review, Laptop review of SemEval 2014, Restaurant reviews of SemEval 2014, 2015, and 2016	GCN, RNN
[41]	Aspect-Based Sentiment Analysis	SemEval 2014 (domain laptop and restaurants) and Twitter	Dual GCN
[42]	Aspect-Based Sentiment Analysis	SemEval 2014 (domain laptop and restaurants)	Sentic GCN

Table 1 shows previous research on sentiment analysis on market topics. Based on the previously published research, this study will discuss the product marketplace in Indonesia with a sentiment analysis approach. The dataset used was obtained from Twitter a social media platform to get the latest data on marketplace topics. The classification methods used are Support Vector Machine and Naive Bayes which are one of the best choices when faced with sentiment analysis cases.

Despite the growing online market, understanding consumer sentiment through social media remains a challenge that this study aims to address. This research provides an interpretation of the sentiment of marketplace users, especially the Tokopedia, Lazada, and Shopee platforms. Interpretation using sentiment analysis approach using Support Vector Machine (SVM) and Naive Bayes methods. The topics focused are on service and delivery of goods.

The contribution of this research lies in its reference to other studies on handling marketplace customer responses in the form of comments on social media. This is utilized as an evaluation of the marketplace in the field of marketplace services and delivery. Sentiment analysis is crucial as it is one of the approaches that can be employed to assess customer responses on social media. Furthermore, this research also contributes by comparing labeling techniques for sentiment analysis, comparing customer satisfaction within the scope of services and delivery, and comparing suitable sentiment analysis methods applied in marketplace cases.

2. METHODS

The stages of research from data capture to system model evaluation are shown in Fig. 1. Fig. 1 shows the research stages of data collection obtained from Twitter (X) using Colab Google. The data goes through a preprocessing stage for data cleaning. The results found sentiment scores using the transformer, TextBlob, and VADER libraries. The results of sentiment labeling are evaluated by evaluators manually. Data goes through the feature extraction stage using TF-IDF (Term Frequency-Inverse Document Frequency). The data is then modeled using manual labels with SVM and Naive Bayes methods.

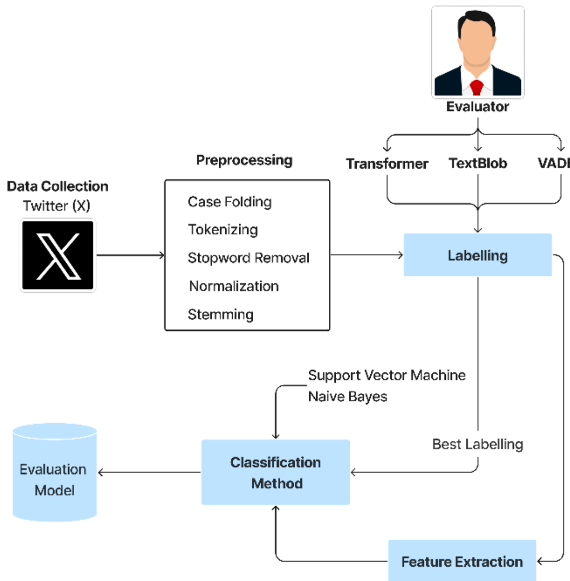


Fig. 1. Roadmap research

2.1. Data Collection

The data used in this study came from Twitter (X) in the form of a CSV. Data obtained is 2057 data on August 27, 2023. The data obtained consists of several attributes are shown in Table 2.

Table 2. Feature item description

Item	Description
Created Tweet	Date tweet was posted Twitter (X)
ID Account	ID on Twitter (X)
Tweet	The Twitter (X) post
Reply Count	Posts that are replied to by comments
Retweet Count	Reshared posts
Favorite Count	Favorite posts

Table 2 shows attribute items in the data obtained, such as Created Tweet, Account ID, Tweet, Reply Count, Retweet Count, and Favorite Count for analysis. The obtained attributes were selected in the study to elaborate on the research data objectives more specifically. For example, the Created Tweet which describes the time the data was uploaded, the ID Account which proves the accounts are different from one another, and Tweets containing the context of the substance of the posts containing sentiment. Other attributes that influence to emphasize how strongly the post is approved by other users include Reply Count indicating the number of replies to the post, Retweet Count indicating the number of posts retweeted by other users, and Favorite Count indicating the number of users who marked the post as a favorite.

2.2. Data Preprocessing and Labelling

Preprocessing includes cleaning raw data and preparing input data for the algorithm [43]. The dataset needs to the following steps:

- Cleaning: This step involves removing unnecessary elements such as numbers, special characters, punctuation, web links, and user mentions. This will make the text of the post more meaningful in terms of text substance (not links or characters, etc.).
- Case Folding: This converts all characters from the cleaning phase to lowercase, supporting the classification method to work more optimally with regular text types.
- Filtering: This phase has two components. Initially, it removes common conjunctions such as "and," "then," "that," and others, followed by a normalization step where informal words are standardized. This step also helps optimize the classification process to focus on texts containing sentiment (substance).
- Stemming: This process removes prefixes and suffixes from words to bring them back to their base form. This step is more specific so that posts get more basic words from each available word.
- Tokenizing: The final stage divides the sentence into individual word tokens, organizing them in an array.

After preprocessing, data is then labeled. Data labeling in sentiment analysis can be done using transformer [44], TextBlob techniques [16], or VADER [45] for sentiment scores [46] -1 to 1 respectively i.e. negative and positive classes. Comparison of these three labeling techniques on the data used as shown in Table 3 in using Indonesian.

Table 3. Comparision of Transformer, TextBlob, and VADER for labelling

Tweet	Transformer	TextBlob	VADER
hai toppers saat ini tokopedia care belum tersedia layanan c all center namun jika kakak ingin dihubungi melalui sambungan telepon silahkan kakak dapat menginfokan nomor telepon melalui dm ya kami tunggu	Negative	Negative	Positive
materi bencoolen coffee sudah bisa kalian dapatkan di manager warung kreatif berbasis layanan digital tersedia di platform cybers academy pintar strategi penjualan minuman bagi sales profesional tersedia di platform cybers academy tokopedia	Negative	Positive	Positive
ada yang ngeh atau punya asumsi liar knapa driver goceng insentifnya untuk semua layanan apa bakal ada orderan gosend khusuz dari tokopedia	Negative	Positive	Negative
live chat aisyah via bsi mobile email contactus coid terima kasih telah menggunakan layanan kami semoga berkah dan selamat beristirahat wassalamualaikum wrwb rahmadend	Negative	Positive	Positive
kepada pihak manapun termasuk pihak bsi serta lakukan pergantian pin password dan kata sandi secara berkala berikut layanan resmi contact center bsi bank syariah indonesia call whatsapp dengan tanda centang hijau verified	Negative	Negative	Positive

Table 3 shows sample Tweets labeled using transformers, TextBlob, and VADER. These three libraries have different predictions for a given Tweet. This study evaluated the labeling of the three libraries with manual labeling. Because manual labeling on sentiment can result in better accuracy [47],[48]. Manual labeling is considered superior for the purpose of labeling evaluation in sentiment analysis because:

- Human labeling is accurate and reliable as it can understand the context and meaning of the text.
- Manual labeling can identify errors and biases that cannot be interpreted when using labeling techniques in machine learning models.
- Manual labeling can be applied to various types of text, including informal and slang texts that may be difficult to classify by machine learning models.
- Manual labeling can understand complex sentiments that contain figures of speech, sarcasm, irony, and ambiguity.

- Manual labeling can consider text context when labeling, such as topic, author, and audience.

Therefore, manual labeling is proposed as a validation technique due to its accuracy [49] compared to other labeling techniques using machine learning. Additionally, validation using manual labeling can build trust and improve model performance in machine-based labeling techniques. Based on the evaluation results using manual labeling, shown in Table 4.

Table 4. Percentage of sentiment in each labeling technique

Labelling Technique	Positive (%)	Negative (%)	Evaluation (%)
Transformer	24	76	59
TextBlob	95	5	52
VADER	96	4	53

Table 4 shows evaluation results based on manual labeling. The transformer technique gets the highest accuracy compared to TextBlob and VADER at 59% with the number of positive sentiments at 24% and negative at 76%. So, this study used transformer labeling techniques to provide sentiment labeling.

2.3. Feature Extraction

Term Frequency Inverse Document Frequency (TF-IDF), a preprocessing method, evaluates the meaning of words or groups of words in a document. TF assigns values to words in the document and IDF reduces the value of words commonly found in many documents. To enable machine understanding, the data must go through preprocessing steps to turn it into vectors representing individual words, measuring their occurrence in the document [50]. Each word that has passed this stage will be input in the classification method. This makes it easier to classify classifications because each available word carries a weight in each document. The higher the weight obtained on a word, the more likely it is for a text containing that word to belong to a certain class.

2.4. Classification Method

2.4.1. Support Vector Machine

The SVM method has superior classification qualities when using nonlinear SVM. There are four kernels in SVM, namely linear, polynomial, Gaussian/radial basis function (RBF), and sigmoid [51]. The formulas for each are shown in (1), (2), (3), and (4) [52].

$$K\ (ys, yt) = ys\ yt \tag{1}$$

$$k(x_i, x_j) = (x_i . x_j + 1)^d \tag{2}$$

$$k(x_i, x_j) = \exp\ (-\gamma||x_i - x_j||_2 \tag{3}$$

$$k(\mathrm{x}, \mathrm{y}) = \tan h\ (\mathrm{a}x^T y + c) \tag{4}$$

The selection of non-linear kernels was done to compare the four kernels with the cases held in this study. The most important benefits of SVM include the following [53]:

- SVM is effective in the case of high-dimensional data and can overcome complexity with the principle of "maximum margin" which increases generalization. This also happened in this research which applied Twitter data.
- SVM is suitable when training data is limited, focusing on support vectors and minimizing the influence of unimportant or duplicate data.
- SVM has clear decision lines and supporting vectors that help understand the factors that influence classification.
- SVM can be customized by setting parameters such as regularization and kernel to control the complexity and performance of the model.

2.4.2. Naïve Bayes

Naive Bayes classifier is based on Bayes theorem and is a type of supervised learning. This shows the presence (or absence) of unrelated class characteristics, and the presence (or absence) of other characteristics [54]. The Naïve Bayes classifier determines the sentiment of data by assessing the likelihood of positive or negative sentiment for each token based on probability [55]. This also applies to the application of sentiment analysis cases on Twitter data. This method is based on Bayes' theorem as shown in the formula [56],[57]. The formula (5) shows how to calculate the probability of hypothesis A based on condition B. Shows the initial probability of class P(A) from the training data, as well as the conditional probability of the attribute distribution P(A) |B) as the initial probability in each class P(B|A) * P(B).

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{5}$$

2.5. Evaluations

The performance of the model is obtained using a confusion matrix consisting of precision, F1-Score, and method accuracy [17] with formulas (6), (7), (8), and (9) [57].

$$Accuracy = \frac{(TP + TN)}{(\mathrm{TP} + \mathrm{FP} + \mathrm{FN} + \mathrm{TN})} \tag{6}$$

$$Precision = \frac{TP}{(\mathrm{TP} + \mathrm{FP})} \tag{7}$$

$$Recall = \frac{TP}{\mathrm{TP}} + FN \tag{8}$$

$$F1 = 2\, x\, precision\, x \frac{recall}{\mathrm{precision}} + recall \tag{9}$$

Precision measures how accurately the model identifies true positives from all the positives predicted by the model. In this case, precision measures how many of all the positive sentiments identified by the model are truly positive. Meanwhile, recall measures how well the model identifies all true positive cases. In this case, recall measures how many of the existing positive sentiments are successfully identified by the model. F1-score indicates the average result between precision and recall. It provides an overall picture of the model's performance by considering both precision and recall. Meanwhile, accuracy measures how well the model can correctly classify all sentiment categories, whether positive or negative. In this case, accuracy provides an overview of how well the model can predict sentiments correctly overall. TP returns a positive result, FP returns a false positive result, TN returns a negative result, and FN returns a false negative result. The matrix illustration obtained from the model prediction is shown in Table 5.

Table 5. Example of a confusion matrix to predict a model

	Positive Prediction	**Negative Prediction**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FN)	True Negative (TN)

Table 5 shows actual comparisons and predictions from the models obtained. If the results of the model prediction and the actual class obtained are the same, the evaluation results will be displayed as True Positive or True Negative. If the results obtained are different, the evaluation results will be displayed as False Positive or False Negative.

3. RESULTS AND DISCUSSION

3.1. Results

Based on the data obtained, several marketplace platforms are widely discussed, including Tokopedia, Lazada, and Shopee. These three marketplaces have become hot conversations on Twitter between August 27, 2023, and before. The amount of data obtained amounted to 2057 Tweet data. Based on these data, the study focused on topics categorized in service and freight forwarding for three platforms as shown in Fig. 2.

Fig. 2 shows an overview of the data collection used in this study. It was shown that the data was taken based on services and delivery for three marketplace platforms in Indonesia, namely Tokopedia, Lazada, and Shopee. The data obtained through the preprocessing stage is carried out using cleaning, case folding, filtering, stemming, and tokenizing techniques. Next, this preprocessing data goes through the labeling stage to categorize classes into positive or negative sentiments. This labeling stage has several techniques that can be used including transformers, TextBlob, and VADER. Based on the tests and evaluation results obtained using manual labeling, the best technique to use is Transformer. Transformer was chosen because it has better accuracy than TextBlob and VADER. Transformers are more reliable at handling sentiment analysis cases for label labeling than TextBlob and VADER because they have more layers and parameters suitable for use in complex cases. Another thing is that this technique is trained on very large data so that it can be more sensitive in reading text for a wide variety of languages and expressions. Labeling of service and delivery data for all three marketplaces is used using this technique.

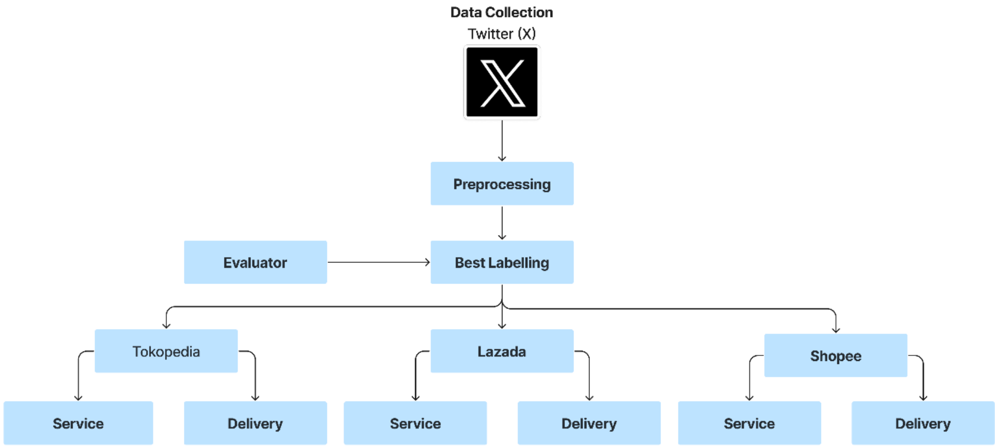


Fig. 2. Data grouping workflow

Labeling is done based on three marketplaces, namely Tokopedia, Lazada, and Shopee. Based on the three marketplaces, they are categorized based on the discussion of services and delivery of goods. The results of labeling performed on the available data are shown in Fig. 3.

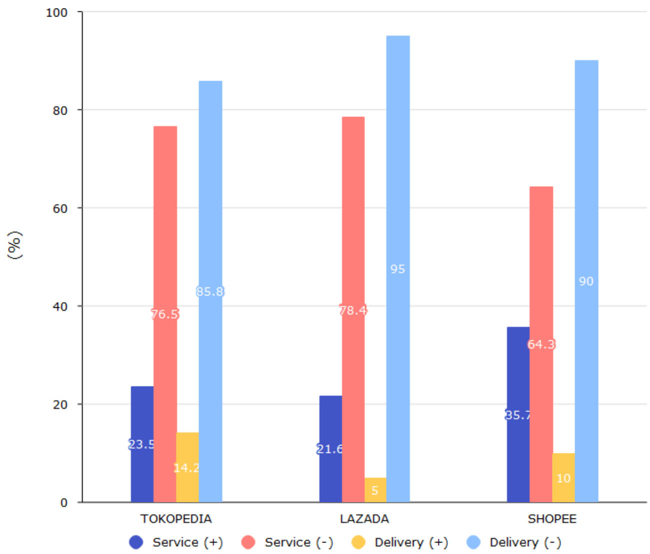


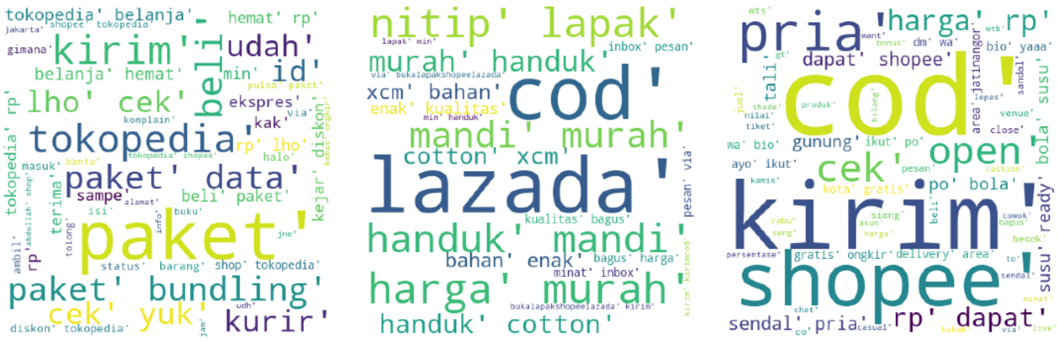
Fig. 3. Sentiment charts on Tokopedia, Lazada, and Shopee discussions

Fig. 3 shows the labeling results by platform with the keywords Tokopedia, Lazada, and Shopee. The three platforms are divided based on user sentiment towards service and delivery of goods. It was found that most users gave negative sentiments towards the existing services and delivery of goods. Services with the most positive sentiment are found on the Shopee platform and followed by Tokopedia and Lazada. Shipments with the most positive sentiment are on the Tokopedia platform, then Shopee, and finally Lazada as shown in Fig. 4.

Fig. 4 shows a set of words against services on the Tokopedia (a), Lazada (b), and Shopee (c) platforms. Common words are cost, service, application service, feedback, independent, and others. A common recurring word on all three platforms is price, buy, or the like. These words certainly present a negative perspective of users on marketplace platforms, especially Tokopedia, Lazada, and Shopee. The set of words for delivery from the three platforms is shown in Fig. 5.

(a) (b) (c)

Fig. 4. Word cloud for service on Tokopedia (a), Lazada (b), and Shopee (c)



(a) (b) (c)

Fig. 5. Word cloud for delivery on Tokopedia (a), Lazada (b) and Shopee (c)

Fig. 5 shows a set of words against delivery on the Tokopedia (a), Lazada (b), and Shopee (c) platforms. Common words that appear in the collection of words with discussions of shipping goods are cod, send, package, courier, cheap, price, stall, and others. Common words that repeatedly appear on all three platforms are COD, Send, Courier, or the like. These words are standard words that appear in the discussion of shipping goods on the three platforms.

Most of the words mentioned in WordCloud are domination words in the whole text which mostly contain negative meanings as in Fig. 3. After labeling the data, go through the feature extraction stage to calculate word trends that appear in the document. It is necessary to know the sensitivity caused by the volume of words in the class label used.

3.2. Classification and Evaluation

The classification methods used are SVM and Naive Bayes. This research uses the sci-kit learn library provided by Python programming on the implementation of SVM [58] and Naive Bayes methods. This study used 10-fold validation and split data on training and testing data, namely 70:30, 80:20, and 90:10. The data sharing is intended to see the best accuracy given to each method. The performance of the classification model is performed to determine the curation, precision, recall, and F1-score as shown in Fig. 6.

Fig. 6 shows the test results of SVM methods and Naïve Bayes. Testing uses split data between the amount of training data and testing data to be used on the model. The first formula is 70% training data and 30% test data, the second formula is 80% training data and 20% test data, and finally 90% training data and 10% test data. SVM methods consist of Linear, RBF, Polynomial, and Sigmoid. The tests carried out were in the form of positive and negative precision, positive and negative recall, positive and negative f1-score, and method accuracy. The average accuracy produced in these two methods is 80.4%. The average accuracy produced by the SVM method as a whole is 80.9% and Naive Bayes is 79.7%. This shows that SVM and Naive Bayes methods are reliable in the case of sentiment analysis. The best accuracy in testing is shown in SVM Polynomial with a 70:30 data split of 84%. SVM with a Polynomial kernel provides the best accuracy when compared to other non-linear kernels [59]. The lowest accuracy is shown in SVM Linear with a 90:10 data split of 75%.

The highest positive f1-score is found in Linear SVM with an 80:20 split data of 51% and the highest negative f1-score in Polynomial SVM with a 70:30 data split of 91%. Split data for 70:30, 80:20, and 90:10 has better performance due to the effect of sufficient training data volume, overfitting prevention, and performance validation performed on test or training data in datasets. The confusion matrix at its best accuracy is shown in Fig. 7. The test data used is 30% taken based on the amount of data available.

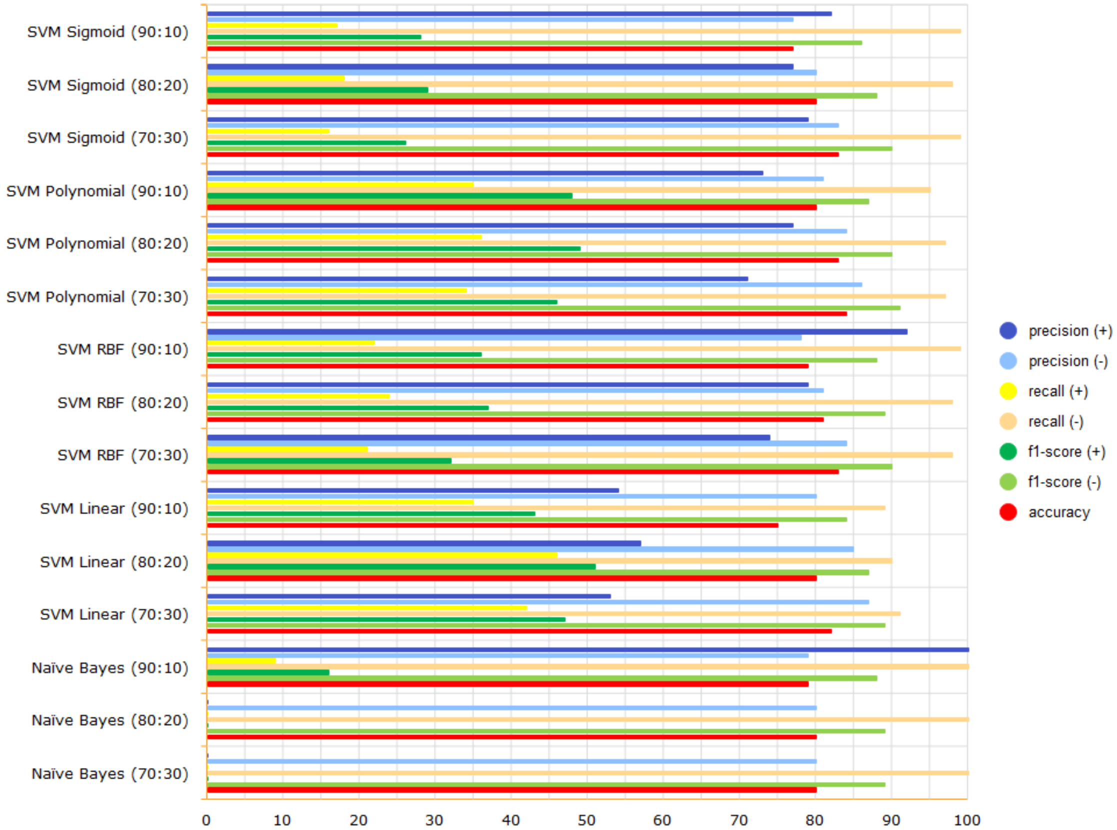


Fig. 6. Comparison of SVM and naïve bayes method performance

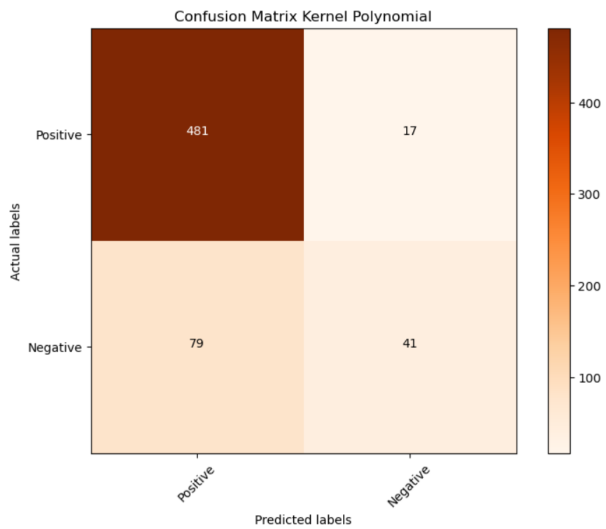


Fig. 7. Confusion matrix with the best accuracy

Fig. 7 shows 618 testing data taken from 30% of the total data. It was shown that the predictions were false positive 79, false positive 481, false negative 17, and true negative 41. The method with the lowest accuracy results is shown using the confusion matrix in Fig. 8.

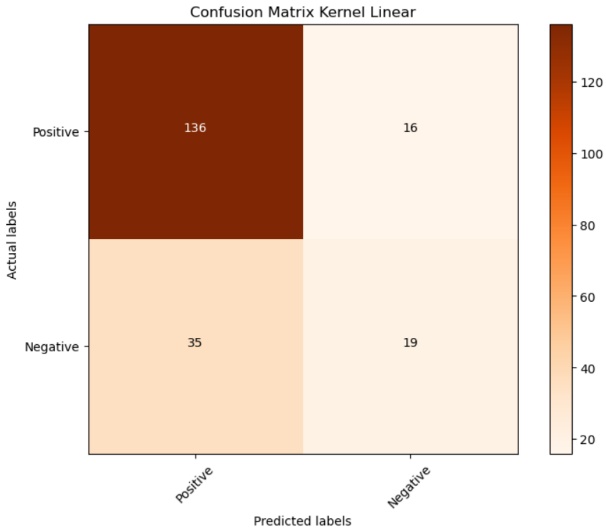


Fig. 8. Confusion matrix with the lowest accuracy

Fig. 8 is the confusion matrix with the lowest accuracy in the method. It was positive with a false prediction of 35, positive with a correct prediction of 136, negative with a false prediction of 16, and negative with a correct prediction of 19.

When a positive review or comment is identified as a false negative, this can cause confusion among consumers. Consumers may be confused as to the actual quality of the product or service. Consumer trust in review and recommendation systems can be eroded if they feel that sentiment analysis is unreliable. In addition, consumers may avoid such products or services because they are perceived to have negative sentiments, when in fact they do not. Misclassified sentiment information can obscure a business's view of customer needs and wants. This can make business decision-making more difficult and inaccurate. Whereas if a negative review or comment is classified as a false positive, the business may not be aware of the actual problem and fail to make the necessary improvements. In the long run, this can lead to a decrease in the quality of the product or service due to the failure to identify and respond to negative feedback from customers. Another thing is that reliability and trust in the system can be eroded. This can reduce the effectiveness of the system in providing accurate insights to the business. As well as can also lead to wrong strategies or inappropriate actions. This can potentially damage a business's reputation in the long run.

3.3. Discussion

A study revealed the use of the Naive Bayes method to conduct sentiment analysis on E-Commerce can provide an accuracy of 72% [60]. Other research for this method conducted comparative review analyses on tourism domains with 80% and 64% accuracy for the first and second tourism sites respectively. While the application of the Naive Bayes method for this study was able to prove the average accuracy obtained from the entire case of 79.7% [61]. This can be affected by the amount of data and the complexity of the data available. While on the application of the SVM method, A study on sentiment analysis of market predictions in order to find out Tweets about finance in Turkish. SVM as one of the methods used gets an accuracy result of 89% [62]. A study revealed to use of linguistic rules-based feature selection methods in tourism reviews. One of the methods used is SVM which can produce an accuracy of 93.5%. While this study provides the best accuracy on SVM of 84%. As with Naive Bayes, this can happen due to factors such as the amount of data, the number of attributes, and the complexity of the data [63]. The comparison of these two methods for sentiment analysis cases is shown in research that discusses Cosine Similarity film recommendations using the Naive Bayes and SVM methods. The results of the study proved that the accuracy of SVM was superior to Naive Bayes, which was 98.63% and 97.33% respectively [64]. This is similar to the results of this study which proves that SVM has a better performance than Naive Bayes in the case of sentiment analysis.

The data obtained on Twitter (X) is 2057 with the Tokopedia, Lazada, and Shopee marketplaces chosen because they are the dominant marketplaces in Indonesia and processed using a sentiment analysis approach. The sentiment class labeling process uses the BERT type transformer technique because it has the best fit when compared to TextBlob and VADER labeling techniques. The evaluation used to test it is using manual labeling. The classification models used are non-linear SVM and Naive Bayes methods. Between the two methods, the SVM method has a higher accuracy than Naive Bayes. However, SVM has the disadvantage of long program computation time when compared to Naive Bayes. SVM has high accuracy because it can find complex decision boundaries in a high feature space, making it suitable for complex classification problems. Likewise, SVM requires longer computational time because SVM seeks the optimal solution by looking for the best hyperplane that separates classes, which requires an intensive optimization process. Likewise, Naive Bayes have lower accuracy due to the nature of Naive Bayes and are not always able to handle dependencies between features well. However, because of its simplicity, the method can have faster computation times. However, these two methods are suitable for use in the same case as the sentiment analysis approach model [21]. This study has limitations that will be recommendations for future similar studies because it has limitations on the amount of data and language barriers. So, the advice given for similar research in the future is to conduct language analysis using linguists, the data used can be from more platforms, and the objects studied can be reproduced.

4. CONCLUSION

This study retrieved data about the marketplace on the Twitter (X) platform on August 27, 2023. The data obtained was 2057. The data obtained is grouped into three marketplaces in Indonesia, namely Tokopedia, Lazada, and Shopee by paying attention to service and delivery of goods. The data obtained is preprocessed and then given a class label. Class labeling techniques are performed using Transformers, TextBlob, and VADER. However, among the three is taken the best. The best technique for labeling is obtained using testing against manual labeling. Transformers have better accuracy than other labeling techniques. Transformer was chosen because it has better accuracy than TextBlob and VADER. Transformers are more reliable in handling sentiment analysis cases for label labeling than TextBlob and VADER because it has more layers and parameters suitable for use in complex cases. In addition, this technique is trained on very large data so that it can be more sensitive in reading text for various languages and expressions. Among the three platforms, labeling results show that most users are dissatisfied with the service and delivery of goods. However, among the three, Shopee received the most positive sentiment towards services and Tokopedia received the most positive sentiment towards shipping goods. Words obtained based on service talks include prices, services, application services, feedback, independence, and others. As for the delivery of goods, common words appear such as COD, shipping, package, courier, cheap, price, and others.

After being labeled, the data will be processed using the extraction feature to see the word trends that exist in the sentiment of each existing data using TF-IDF. This will provide recommendations for word patterns with the number of words in the dataset that will be input into the classification method. Then the data will be given machine learning through a training and testing process with comparison data of 70:30, 80:20, and 90:10 using SVM and Naive Bayes methods. Based on the evaluation results, very good accuracy was obtained for both methods. The average accuracy of SVM is higher than Naive Bayes, it's just that the computation time used with the SVM method is longer when compared to the Naive Bayes method. This proves that these two methods are suitable for use in the case study sentiment analysis approach with an average accuracy in each case obtained by SVM and Naive Bayes of 80.9% and 79.7% respectively. It's just that in this case, SVM has a higher level of accuracy than Naive Bayes.

However, this study still has weaknesses in labeling techniques and the scope of data is still limited to Indonesian users on Twitter. This could be a recommendation for future research. Some research results in the form of negative sentiments are expected to be input for the marketplace in terms of service and delivery such as costs, cod, couriers, and shipping. Likewise, the positive sentiment obtained can be input to build a better image in the marketplace itself. This will be a marketplace evaluation so that it can have a more pronounced impact on customers.

Acknowledgments

Thank you to the University of Mataram for supporting this collaborative research.

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BIOGRAPHY OF AUTHORS

Muhammad Mujahid Dakwah, serving as a permanent lecturer in the Management Program at the Faculty of Economics and Business, Universitas Mataram. With expertise in the field of Digital Marketing. Email: mujahid.fe@unram.ac.id. ORCHID: https://orcid.org/0000-0002-7619-5364. SINTA id: 6172847.

Asno Azzawagama Firdaus, Graduate student at Universitas Ahmad Dahlan majoring in Informatics Engineering since September 2022. Graduated from Mataram University, Indonesia, in January 2019, with a Bachelor's degree in Informatics Engineering**.** Email: asnofirdaus@gmail.com. ORCHID: https://orcid.org/0009-0005-1564-6167. SCOPUS ID: 58667521800.

Furizal, Received the bachelor's degree from the Department of Informatics Engineering, Universitas Islam Riau, in 2022, and the master's degree from the Department of Informatics, Universitas Ahmad Dahlan, in 2023. His research interests include artificial intelligence, fuzzy sets, control systems, Internet of Things, and web development. Email: furizal.id@gmail.com. ORCHID: https://orcid.org/0000-0001-6042-3986. SCOPUS ID: 58069155200.

Rangga Alif Faresta, Master's Student at Monash University in Digital Learning, Faculty of Education. Flexible and polished Junior Research Associate promoting well-developed Teaching Research and Science skills. Email: rfar0018@student.monash.edu. ORCID: https://orcid.org/0009-0005-6535-2300.