

Sentiment Analysis of Marketplace Application Reviews Using Support Vector Machine (SVM) and K-Nearest Neighbors (KNN)

Arief Ichwani¹, Munawar², Rilla Gantino³

^{1,2} Informatics Engineering , Esa University Superior

³ Master of Accounting , Esa University Superior

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ABSTRACT

Shopee is one of the most popular online marketplaces in Indonesia, with more than 103 million users in 2023. Most users consider factors such as customer reviews, ratings, prices, and free shipping promotions before making a purchase. Analyzing user reviews is essential to understand consumer perceptions of services, identify satisfaction or dissatisfaction, and detect potential issues that need to be addressed. However, sentiment analysis faces challenges in processing text with diverse language styles, structures, and informal expressions. To overcome these challenges, this study applies machine learning algorithms—Support Vector Machine (SVM) and K-Nearest Neighbors (KNN)—for classifying sentiment in Shopee user reviews. Data labeling using the Lexicon InSet method produced 9,509 positive reviews (47.55%), 7,686 negative reviews (38.43%), and 2,805 neutral reviews (14.03%). Based on the Confusion Matrix results, SVM outperformed KNN, particularly in classifying negative and neutral sentiments with higher accuracy. These findings indicate that SVM is a more effective and efficient model for sentiment analysis of user reviews on the Shopee platform[1].

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Corresponding Author:

Arief Ichwani

Faculty of Computer Science

Esa University Superior

West Jakarta, Indonesia

Email: arief.ichwani@esaunggul.ac.id

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1. Introduction

With development rapid growth of e-commerce, especially in the Southeast Asia region , reviews and responses users be one of very important data source for company in understand quality service as well as satisfaction users to application . Reviews users can reflect experience shop in a way directly , giving outlook about excess and weakness from features offered by marketplace platforms, such as Shopee.

Shopee is one of the the most popular marketplace application in Indonesia. In 2023 , the number of Shopee users in Indonesia reached 103 million , making it the platform with users the most in the country [1] . With height amount users , the majority buyers on Shopee tend to consider a number of factor important before do purchases , such as evaluation customers (online customer rating), reviews customers (online customer reviews), prices , and free shipping offers send . Factors This become gauge measuring main in choose shop , okay shop normal and star sellers. Although online stores on Shopee have registered and

trusted, consumers still do evaluation alone based on various considerations to ensure quality and trust in shopping.

Analysis to review users can help a company identify contributing factors to successful service or reflect potential problems that need to be addressed quickly [3]. This data can be utilized for increasing performance, application, repair services, and adjusting marketing strategies. However, for managing and extracting information valuable from a very large and varied number of reviews, a precise and efficient method is required [4][5].

One of the common methods used is sentiment analysis, which aims to identify emotion or opinion behind every review user. This gives useful mapping for understanding user perception of a product or service, whether they feel satisfaction, dissatisfaction, or give a neutral response [6]. Sentiment classification is divided into three main categories, namely positive, negative, and neutral. Positive reviews usually reflect satisfaction with applications, often related to availability of products, convenience of transactions, or speed of shipping. Negative reviews, on the other hand, indicate problems faced by users, such as technical disturbances, delayed delivery, or mismatched products [5][6]. Meanwhile, neutral reviews tend to contain an objective view that does not convey strong emotion, but is still relevant in giving input about user experience in a general way [3][2].

However, the main challenge in sentiment analysis is how to process highly varied text data in language, structure, and writing style. Users often use informal language, slang, or abbreviations, which make it difficult to interpret automatically. Therefore, it is necessary to use powerful Natural Language Processing (NLP) techniques as well as machine learning algorithms capable of handling variation well. NLP techniques such as Word2Vec can help increase accuracy in processing language experience [3]. The importance of feature selection in dealing with inconsistent data is balanced, where the more appropriate sentiment analysis can be achieved with a combination of appropriate features and powerful algorithms [6].

Two common algorithms used in sentiment analysis are Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). SVM is a machine learning algorithm for finding the best separating hyperplane between existing classes in data, such as positive and negative sentiment. SVM is very effective for handling data with high dimensions, such as review text, which can contain thousands of features in word forms [3], [4]. This algorithm's own ability to overcome overfitting is especially useful on complex datasets [2].

Temporarily, KNN is an algorithm based on the closest neighbor, where one determines the class from a new data based on the majority class from the closest neighbors. Although simple, KNN can give competitive results, especially when the data is analyzed in terms of size and distribution. No too varies [8][5]. This algorithm works by comparing word patterns in new reviews with reviews that have been known sentiment, and classifying new reviews based on similarities. In context analysis of review users on Shopee, SVM and KNN are often used to determine sentiment and evaluate the effectiveness of improvement strategies for services on the application.

This study aims to compare the accuracy and performance of the second algorithm in doing sentiment analysis on reviews of the Shopee marketplace application. With this comparison, this research can give an outlook about which method is better effective in categorizing review users, so that it can give more appropriate recommendations for developer application in repair experience shop user. This study is also expected to contribute to the improvement of service quality through utilization of review data in a more optimal way, which in the end will support growth of e-commerce businesses like Shopee [9][9].

2. Research Method

The data collection method in this research is secondary data collection from the Google Play Store app Shopee. As for the steps to take in doing sentiment analysis using Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), as following:

1) Data collection

Step:

- a) Shopee review data can be obtained through scraping from the Shopee site or using available datasets in a public way.
- b) Data includes text reviews and sentiment labels (positive, negative, neutral).

2) Data Preprocessing

Step:

- a) Cleanup: Delete special characters, numbers, and signs that are not relevant.
- b) Case Normalization: Change text review to lowercase to make it more consistent.
- c) Stop Word Removal: Remove unnecessary words that have no significant meaning such as "and", "or", "to", etc.

- d) Stemming/Lemmatization: Change words into form base For consistency word analysis (for example , " main " becomes "main").
Feature Extraction
 Step:
 - a) Change text review become representation numerical that can used For machine learning modeling .
 - b) Method commonly used :
 - c) Bag of Words : Build representation based word frequency .
 - d) TF-IDF (Term Frequency-Inverse Document Frequency): Calculating weight the importance of words based on frequency its emergence .
- 3) Split (Train-Test Split)
 Step:
 - a) Divide the dataset into two parts : training data (training set) and test data (testing set) so that it can evaluate model performance with Good .
 - b) Typically , training data taken as much as 80%, while the test data is as much as 20%.
- 4) Model Development (Training)
 Steps (SVM):
 - a) Apply Support Vector Machine (SVM) to train the model using training data .
 - b) Select the appropriate kernel (linear, RBF, polynomial), adjust with data and goals analysis .
 Steps (KNN):
 - a) Apply K-Nearest Neighbors (KNN) algorithm for train the model on training data .
 - b) Determine optimal k value (number neighbor nearest) to more classification accurate .
 Tools:
 - a) For SVM, use ` svm.SVC ( ) ` from Scikit-learn.
 - b) For KNN, use ` KNeighborsClassifier ( ) ` from Scikit-learn.
- 5) Model Testing
 Step:
 - a) After the model is trained , do testing on test data for measure how much good model can predict sentiment that has not been Once seen previously .
 - b) Compare model prediction with original labels on test data.
 Tools:
 - a) Use the ` predict( ) ` method of the trained model For predict results sentiment on test data.
- 6) Model Evaluation
 Step:
 - b) Measuring model performance using metric evaluation like :
 - c) Confusion Matrix: For see classification right and wrong of the model.
 - d) Accuracy: Percentage correct prediction .
 - e) Precision, Recall, and F1-Score: Metrics important additions in evaluation classification .
- 7) Model Optimization
 Step:
 - 1) Do model optimization for increase accuracy and performance .
 - 2) A number of method optimization includes :
 - a) Grid Search or Random Search for find the best parameters on SVM and KNN.
 - b) Cross-validation for ensure model stability and avoid overfitting.
 Tools:
 - a) Use ` GridSearchCV ` from Scikit-learn to best hyperparameter search .
- 8) Visualization of Results
 Step:
 - b) Visualize results analysis sentiment For more easy understood .
 - c) Use visualization like WordCloud For display frequently used words appear in reviews .
 - d) Use Confusion Matrix and ROC Curve to illustrate model performance .
 Tools:
 - a) Use Matplotlib, Seaborn, or WordCloud For visualization .
- 9) Conclusion and Documentation of Results
 Step:
 - b) For conclusion from results analysis sentiments that are carried out .
 - c) Document it the whole process of data collection up to model evaluation .

- d) Tell me which model is better effective in analysis sentiment between SVM and KNN and recommendation For future improvements .

3. Result and Discussion

3.1 Data Collection

This study utilizes review data collected from the Shopee application available on the Google Play Store. The retrieved data were then converted into Microsoft Excel format for further processing and analysis. From the data collection process, a total of 20,000 user reviews were initially obtained. After performing data cleaning and duplicate removal, the final dataset consisted of 15,209 unique records that were ready for analysis. The review data were collected using the web scraping method with the assistance of the “google-play-scraper” library, which automatically extracts user reviews from the Google Play Store based on the latest review order (sort = Sort.NEWEST)[11].

This approach ensured that the dataset reflected the most recent user opinions and experiences, allowing the sentiment analysis to capture current trends in user satisfaction and feedback dynamics. In addition, the automated scraping process minimized manual collection errors and improved the efficiency and accuracy of data acquisition.

3.2 Preprocessing

Stages This is stages crucial aiming For ensuring clean , consistent , and ready data For analysis more deep . Collected data need processed through a number of stages *data preprocessing* that is *cleansing* , *case folding* , *tokenizing* , *normalizing* , *stopwords* , and *stemming* [12].

- a) Cleansing, case folding , and normalization
- Cleansing stages is For remove elements that are not relevant so that text become more clean and easy analyzed . The results from stages *cleaning* .

Table 1. Results of *Cleaning* , Case Folding, and Data Normalization

Review Text	cleaning	case_folding	normalisasi
Now you don't have to worry about shopping online at Shopee anymore. It's always safe and secure. Because there is a money back guarantee if the item is not as expected. There is a free return policy. Thank you Shopee	Now you don't have to worry about shopping online at Shopee anymore, it's always safe and controlled because there is a money back guarantee if the item is not as expected, there is free return of goods, thank you Shopee	Now you don't have to worry about shopping online at Shopee anymore, it's always safe and controlled because there is a money back guarantee if the item is not as expected, there is free return of goods, thank you Shopee	Now you don't have to worry about shopping online at Shopee anymore, it's always safe and controlled because there is a money back guarantee if the item is not suitable, there is free return of goods, thank you Shopee
I've only tried using Shopee once, but it's tiring. Orders don't match estimates, and shipping takes a long time. I'm not comparing it to the blue shop next door. Even though they're overloaded, their delivery service is always on time.	I've only tried using Shopee once, but it turns out I'm tired. The order doesn't match the estimated delivery time. I don't want to compare it with the blue shop next door. Even though it's a load oper, the delivery service is always on time.	I've only tried using Shopee once, but it turns out that the order doesn't match the estimated delivery time. I don't want to compare it with the blue shop next door, even though the delivery service is always on time.	I've only tried using Shopee once, but it turns out that the order doesn't match the estimated delivery time, so I don't want to compare it with the blue shop next door, even though they use the shipping service, it's always on time.

really makes all purchasing and payment processes easier ðŸˆ¸	greatly simplifies all purchasing and payment processes	greatly simplifies all purchasing and payment processes	greatly simplifies all purchasing and payment processes
Shopee is getting slower..	Shopee is getting slower	Shopee is getting slower	Shopee is getting slower
I am very satisfied shopping at Shopee, thank you ðŸ™	I am very satisfied shopping at Shopee, thank you	I am very satisfied shopping at Shopee, thank you	I am very satisfied shopping at Shopee, thank you.
Can you pay on the spot or pay when the goods arrive	You can pay on the spot instead of paying when the goods arrive	You can pay on the spot, you don't have to pay when the goods arrive	can pay on the spot or not pay when the goods arrive

b) *Stokenizing , stopword removal ,*

Table 2. Stopword Results

tokenize	stopword removal
['service', 'courier', 'very', 'bad', 'to', 'seller']	['service', 'courier', 'bad', 'seller']
['new', 'try', 'once', 'use', 'shopee', 'apparently', 'rewarded', 'order', 'no', 'according to', 'long estimate', 'delivery', 'yes', 'not', 'want', 'compare', 'same', 'shop', 'blue', 'next door', 'even though', 'operate', 'load', 'service', 'send', 'yes', 'always', 'right', 'time']	['try', 'use', 'shopee', 'kapuk', 'order', 'according to', 'estimated time', 'delivery', 'yes', 'compare', 'shop', 'blue', 'next door', 'oper', 'load', 'service', 'send', 'yes']
['very', 'make it easier', 'all', 'process', 'purchase', 'and', 'payment']	['make it easier', 'process', 'purchase', 'payment']
['shopee', 'more', 'slow']	['shopee', 'slow']
['I', 'very', 'satisfied', 'shopping', 'at', 'shopee', 'thank', 'thank you']	['satisfied', 'shopping', 'shopee', 'receive', 'thank you']
['can', 'pay', 'at', 'place', 'no', 'pay', 'yes', 'pass', 'goods', 'already', 'arrived']	['pay', 'pay', 'yes', 'pass', 'goods']

c) *and stemming .*

In stages This done *s temming* namely the process of changing words in A text become form basically (*root word*). This process aim For simplify words that have form derivatives[13] . The results are is as following :

Table 3. Stemming Results

stopword removal	steming_data
['service', 'courier', 'bad', 'seller']	bad courier service sell
['try', 'use', 'shopee', 'kapuk', 'order', 'according to', 'estimated time', 'delivery', 'yes', 'compare', 'shop', 'blue', 'next door', 'oper', 'load', 'service', 'send', 'yes']	Try using Shopee Kapuk, order according to the estimated delivery time compared to the Blue Shop, which operates the delivery service.
['make it easier', 'process', 'purchase', 'payment']	easy buy pay process
['shopee', 'slow']	Shopee Lot
['satisfied', 'shopping', 'shopee', 'receive', 'thank you']	satisfied shopping at Shopee, thank you
['pay', 'pay', 'yes', 'pass', 'goods']	pay when you receive the goods
['sis', 'please', 'men', 'non', 'activate', 'sea', 'bank', 'wife', 'buy', 'pridok', 'assessment with', 'sticker', 'shopee', 'receive', 'ordered', 'activate', 'sea', 'bank']	Sis, please deactivate Sea Bank, wife buys Pridok, assessment with Shopee sticker, accepts, told to activate Sea Bank, told to activate ES loan,

'ordered', 'active', 'espinjam', 'profit', 'husband', 'go home', 'say', 'fraud', 'code', 'otp', 'sent', 'fraudster']	fortunately husband comes home, says fraud, OTP code, sends fraud
['service', 'shipping', 'cheap']	cheap shipping service
['application', 'good', 'sometimes', 'like', 'free', 'shipping']	good app sometimes likes free shipping
['shopping', 'online', 'shopee', 'scared', 'safe', 'controlled', 'guarantee', 'money', 'goods', 'according to conditions', 'free', 'returns', 'goods', 'thank you', 'shopee']	Shopee online shopping is safe, guaranteed money, goods are as is, free to return goods, thank you Shopee

d) Data Labeling

Data labeling is a crucial process in data analysis . At this stage this , data labeling will be use *Lexicon InSet* For grouping sentiment- related data in *the marketplace* Shopee to in three category that is positive , negative and neutral . Furthermore , the results data labeling by *Lexicon InSet* will validated by experts Language For ensure its accuracy[14] .

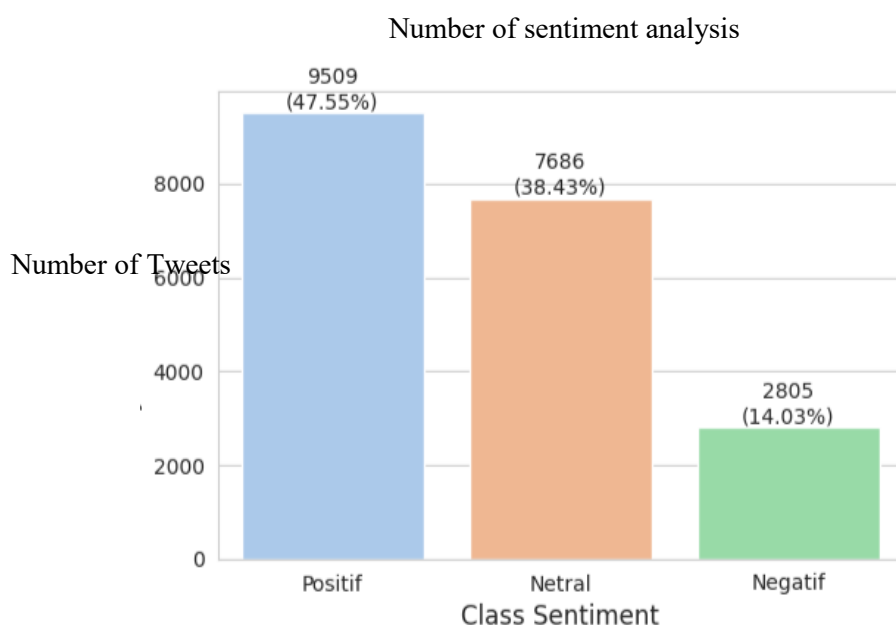


Figure 1. Number Analysis Sentiment from Shopee

Figure 1 shows distribution sentiment based on results labeling use *Lexicon* in diagram form . The majority *Tweet* has sentiment positive as big as 47.55 % , which shows that review related Shopee on Google Play Store dominated by positive sentiment . Meanwhile that , sentiment negative (38 , 43 %) and sentiment neutral (14.03 %) reflects No show clear feeling[15].

e) Training Data and Data Testing

After the labeling process finished , the data will be shared become two part namely training data and test data, before enter stage training using SVM, KNN, and Naïve Bayes models . Training data functioning as data set used For training *machine learning* models , enabling algorithm learn patterns , features , and relationships between variable . While that , test data is used For measure model performance after the training process finished , without follow as well as in stage learning . In study here , the data is shared with proportion of 80:20, as explained following This :

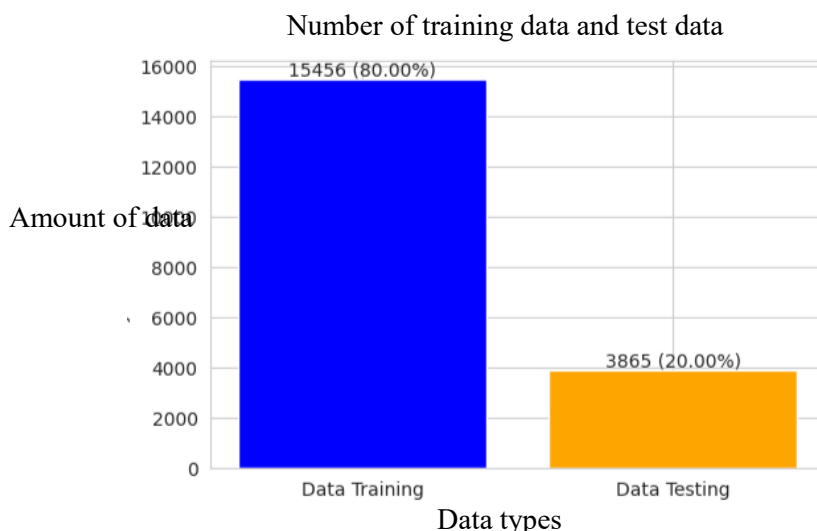


Figure 2. Number of Training Data and Test Data

In Figure 2 above , the *review data* is the training data . is 15,456 reviews and the *review data* that becomes the test data is 3,865 *reviews* .

f) Model Evaluation

At the stage previous data testing , the code used also includes visualization *Confusion Matrix* for show distribution error predictions . Here This is results SVM model evaluation in do classification , which is displayed through *Confusion Matrix* [16].

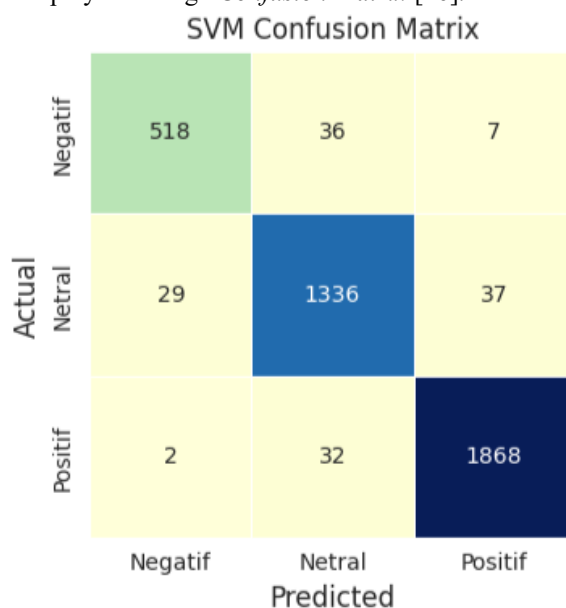


Figure 3. SVM Confusion Matrix

Confusion Matrix above show performance of the SVM model in classify sentiment become three category , namely positive , negative , and neutral . Of the total predictions , the model was successful classify 518 samples with Correct as negative , but there are 36 samples falsely predicted negative as neutral and 7 samples falsely predicted negative as positive[17] . For category neutral , capable model predict with Correct as many as 1,336 samples , however there are 29 samples wrongly predicted neutral as negative and 37 samples wrongly predicted neutral as positive . Meanwhile that , in the category positive , the model shows performance the best [18].

Total 20,000 samples the predicted with true , but Still there are 29 samples false positive prediction as negative and 37 samples false positive prediction as neutral [19]. Visually , the color in This *Confusion Matrix* represent amount sample in every category predictions . The more dark color blue , more and more tall amount classified samples in cell said . Cell with color darkest blue show the most dominant prediction , namely in the category predicted positive with true (1,868 samples). On the other hand , the more bright show amount more samples a little , as in a mistake classification category negative to positive (7 samples). Colors This help in identify pattern error classification , where the error the biggest appears in the classification category neutral to positive and vice versa , which shows possibility existence similarity pattern between second category This *Confusion Matrix* give clear picture about the areas where the model can improved For reduce error classification , especially in differentiate sentiment neutral and positive[20] .

From the picture The *Confusion Matrix* We can count accuracy and metrics other with use values from The *Confusion Matrix* .

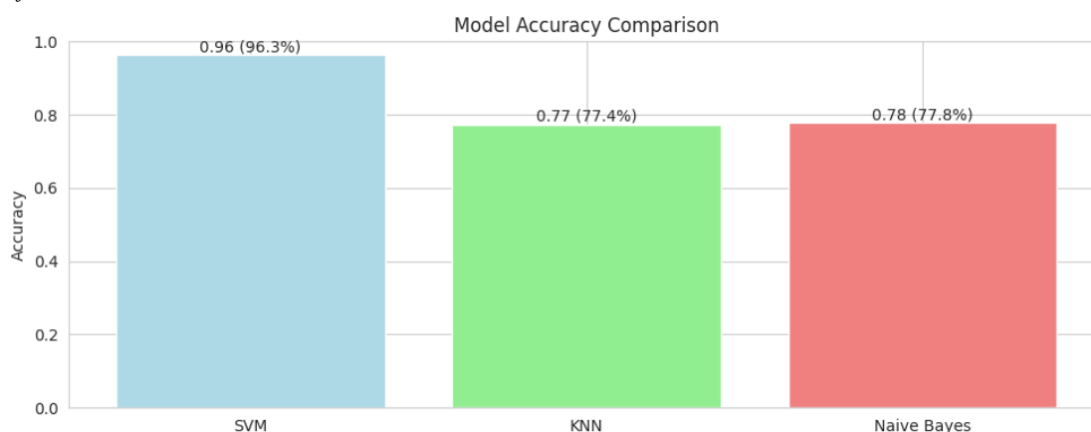


Figure 4. Comparison of Accuracy models

Based on results comparison from Figure 6.16 shows that the SVM model has greater accuracy Good with value of 96.3% compared previously .

	precision	recall	f1-score	support
Negatif	0.944	0.923	0.933	561.000
Netral	0.952	0.953	0.952	1402.000
Positif	0.977	0.982	0.980	1902.000
accuracy	0.963	0.963	0.963	0.963
macro avg	0.957	0.953	0.955	3865.000
weighted avg	0.963	0.963	0.963	3865.000

Figure 5. Classification *Report* for SVM

Report the above classification serve metric evaluation for classification models sentiment SVM model, which was applied to three category sentiment that is negative , neutral and positive [21]. This model get accuracy overall by 96% of all test data. Positive class show performance best with *F1 - Score* of 0.98, which indicates optimal balance between *Precision* (98%) and *Recall* (98%), so the model is capable of recognize sentiment positive with level high accuracy as well as only A little experience error classification . However , in class negative and neutral , *F1 - Score* is 0.93 and 0.95 respectively , which indicates existence

challenge in differentiate second category This with precise . More *precision* low in class neutral (0.95%) and More *recall* low in class negative (0.92%) indicates that the model is still often make error in classify sentiment neutral and not yet fully capable recognize all negative data with true . In overall , results evaluation This show that the model has good performance in identify sentiment positive , but Still need repair in recognize sentiment negative and neutral , especially in increase accuracy classification into categories neutral which is still often miscategorized as sentiment negative or positive[22] .

Besides results from *Confusion Matrix* of the SVM model, in study this is also available results visualization *Confusion Matrix* from use of the KNN model. The following is results from The *Confusion Matrix* .

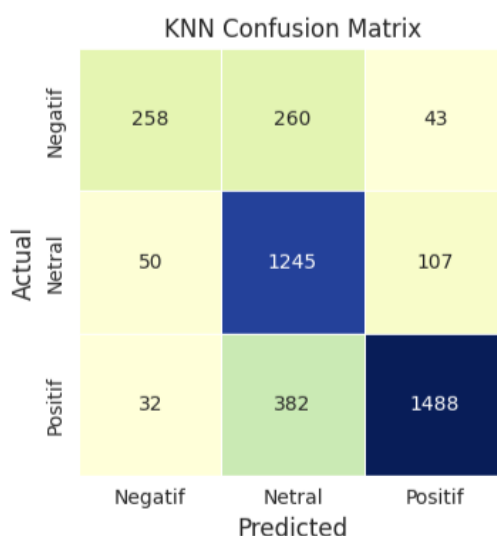


Figure 6. KNN Confusion Matrix

The *Confusion Matrix* in Figure 6.17 shows performance of the KNN model in classify sentiment become three category , namely positive , negative , and neutral . Of the total predictions , the model was successful classify 258 samples with Correct as negative , but there are 260 samples falsely predicted negative as neutral and 43 samples falsely predicted negative as positive . For category neutral , capable model predict with Correct as many as 1245 samples , but there are 50 samples wrongly predicted neutral as negative and 10 samples wrongly predicted neutral as positive [23]. Meanwhile that , in the category positive , the model shows performance at its best , with 1488 samples predicted with true , but Still there are 32 samples false positive prediction as negative and 382 samples false positive prediction as neutral . Visually , the color in This *Confusion Matrix* represent amount sample in every category predictions[24] . The more dark color blue , more and more tall amount classified samples in cell said . Cell with color darkest blue show the most dominant prediction , namely in the category predicted positive with true (1,488 samples) . On the other hand , the more colors bright show amount more samples a little , as in a mistake classification category negative to positive (43 samples) . Colors This help in identify pattern error classification , where the error the biggest appears in the classification category neutral to positive and vice versa , which shows possibility existence similarity pattern between second category This *Confusion Matrix* give clear picture about the areas where the model can improved For reduce error classification , especially in differentiate sentiment neutral and positive [25].

Classification Report for KNN:

	precision	recall	f1-score	support
Negatif	0.759	0.460	0.573	561.000
Netral	0.660	0.888	0.757	1402.000
Positif	0.908	0.782	0.841	1902.000
accuracy	0.774	0.774	0.774	0.774
macro avg	0.776	0.710	0.723	3865.000
weighted avg	0.797	0.774	0.771	3865.000

Figure 7. Classification Report for KNN

Then Report The classification in Figure 7 presents metric evaluation for classification models KNN model sentiment , which is applied to three category sentiment that is negative , neutral and positive . This model get accuracy overall by 77% of all test data. Positive class show performance best with *F1 - Score* of 0.84, which indicates optimal balance between *Precision* (90%) and *Recall* (78%), so the model is capable of recognize sentiment positive with level sufficient accuracy tall as well as only A little experience error classification . However , in class negative and neutral , *F1 - Score* is 0.57 and 0.75 respectively , which indicates existence challenge in differentiate second category This with precise . More *precision* low in class neutral (66%) and More *recall* low in class negative (75%) indicates that the model is still often make error in classify sentiment neutral and not yet fully capable recognize all negative data with true[26] . In overall , results evaluation This show that the model has poor performance Good in identify sentiment positive , and also requires repair in recognize sentiment negative and neutral , especially in increase accuracy classification into categories neutral which is still often miscategorized as sentiment negative or positive .

4. Conclusion

Based on Based on results data processing and results analysis , then conclusion from study This is

- Data labeling is done use method *Lexicon InSet* show that 9,509 reviews (47.55 %) sentiment positive , 7,686 reviews (38.43 %) negative , and 2,805 reviews (14.03 %) neutral .
- Based on results *Confusion Matrix* , SVM more superior in catch pattern sentiment compared to KNN , especially in classify sentiment negative and neutral with more accurate . This is show that the SVM model is a better algorithm accurate and efficient in categorize sentiment review users on Shopee.

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