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Sentiment Analysis of Practo App Reviews using KNN and Word2Vec

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Abstract−The development of technology and communication is used by the community to facilitate daily activities, one of which is in the field of health services. Health services are good enough, but there are still some obstacles that are commonly found, including not allowing to leave the house or a short schedule of doctor consultations. With the presence of health service applications, one of which is Practo, it makes it easier for people to consult online. This convenience makes a lot of reviews regarding the Practo healthcare application. The diversity of opinions on the internet, makes Practo app reviews varied. Therefore, sentiment analysis of Practo app reviews is necessary. In this study, the algorithm used was KNN. The KNN algorithm was chosen because it is very effective if the amount of data is large and easy to implement. The feature extraction used in this study is Word2Vec. Word2Vec was chosen as a feature extraction because it was considered good enough to use because it represented each word with a vector. This research produced the best model built when using stemming with Word2Vec dimensions of 300 and K = 3 values on the KNN parammeter, capable of producing an f1-score of 77.30%.

Keywords: Sentiment Analysis, Practo Application Review, KNN, Word2Vec

1. INTRODUCTION

Technology, communication, and information are growing rapidly along with the times.. Technological advancements are designed to make everyday life easier, both in doing work and getting information. Among the various sectors affected by the 4.0 era, it seems that the healthcare sector has the most to gain from the merging of physical, digital, and biological systems, although this field may be the least prepared to welcome it [1]. Digital health services are growing rapidly in the past 2 years, some digital services have been integrated with health institutions [2].Of course, going to a health institution to see a doctor can treat the pain we suffer, but if we do not have enough free time or the distance of the health institution is far away, especially with the current conditions that force us not to visit crowded places [3].

Sentiment analysis is a type of analysis that uses linguistic computing, text mining and natural language processing with the aim of analyzing sentiment or ratings on a particular product or service [4]. In sentiment analysis, opinions in a text are categorized into categories such as positive, negative, or neutral. [5]. A positive category means that the comments given against the application have good value. Whereas, a negative category means that the comments given against the application have a less good value. However, there is also a neutral category which means that the application has a value that is not too good and not too bad. Through sentiment analysis, people get help in choosing the right health app. By analyzing positive or negative sentiments in reviews, people can gain insights into other users experiences. This research also aims to understand the extent to which sentiment analysis algorithms and techniques are effective in processing health app review data.

Sentiment analysis has many algorithms that can be used. In this research, the feature extraction used is Word2Vec, Word2Vec is good to use as feature extraction because it can represent each word with a vector. Thus, when using Word2Vec the polarity of the score of each word has an important role in the results of sentiment analysis [6]. In research [6] by Ardhian Fahmi Sabani in 2022, explained that Word2Vec feature extraction as a very good feature extraction is used because it represents each word into a vector.

There are several classifications that can be used in conducting sentiment analysis, in this study the classification used is K-Nearest Neighbor. This classification is used because according to research [7] the KNN method is considered a high-quality approach in behavior analysis, especially in sentiment analysis. In research [7] conducted by Imam Prayoga in 2023, it was explained that, the KNN method used in sentiment analysis of Indonesian movie reviews had an f1-score value of 86.98% which means it has accurate results for performing sentiment analysis.

In research [8] by Widi Widayat in 2021 discusses Sentiment Analysis Movie Review using Word2Vec and the Long Sort Term Memory Deep Learning method. In this study, it goes through several preprocessing stages which include converting data into lowercase form, cleaning characters in reviews that do not have sentiment meaning, deleting urls, and also tokenizing the dataset. In the study, the best accuracy value was obtained when using a dimension size of 100 of 88.17% and the lowest accuracy value of 85.86% at a dimension size of 500, which means it is quite good at doing sentiment classification. So that the Long Sort Term Memory method with word2vec can be an option when you want to do research on sentiment analysis with large amounts of data.

In research conducted by Dwi Intan Af'Idah in 2021 [9]. This study investigates how Wod2Vec parameters impact deep learning capabilities in sentiment classification. The research goes through preprocessing starting from the case folding, filtering, tokenization, and stopword removal processes. The study analyzed the influence of Word2Vec architecture on model accuracy with CBOW accuracy value of 97.12% and Skip-gram accuracy value of 96.62%, in another study the influence of Word2Vec evaluation method on model accuracy with Hierarchical Softmax

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accuracy value of 97.16% and Negative Sampling accuracy value of 96.58%, besides that, the study reviewed the influence of Word2Vec dimensions on model accuracy. The results show that dimension 100 has a better effect than dimensions 200 and 300, the value of dimension 100 is 97.10% while the value of dimension 200 is 96.77% and the value of dimension 300 is 96.73%.

Research [10] conducted by Syarifuddin in 2020, using the Naïve Bayes-decision tree-KNN algorithm to discuss public opinion on the impact of the PSBB on Twitter. In this study there are several stages in preprocessing, including convert negation, cleansing, tokenization, case folding, stemming in Indonesian. and stopword removal. The accuracy value of the decision tree is 83.3% while the KNN accuracy value is 80.80% and the Naïve Bayes accuracy value is 80.03%. The precision value of the decision tree is 81.06% while the precision value of KNN is 82.72% and the precision value of Naïve Bayes is 87.54%. While the recall value of the decision tree classification gets a recall value of 87.17% and the recall value in the Naïve Bayes classification gets the lowest value with 62.71%, other recall values in the KNN classification get a value of 74.41%

Another research conducted by Puji Astuti in 2022 [11]. This research describes the application of the KNN algorithm to the sentiment analysis of care protect application reviews. In this study through two preprocessing stages, namely tokenize and stopword filter. In this study, the use of applications in calculating the accuracy value is RapidMiner software in the data processing process. Fold cross validation was used in this study, and to calculate accuracy using the Confusion Matrix. The ROC curve is used to measure the AUC value. Where cross validation is an action taken in finding the accuracy of each method by dividing data test and data train. In this study, the amount of data used was 200 data divided into 100 negative review data and 100 other positive review data. The accuracy value is 81.72% with an AUC value of 0.856, while by changing the K value to K = 20, the accuracy is 81.74% with an AUC value of 0.861. More data is needed to increase the accuracy value.

In Research [12] conducted by Abdul Rozaq in 2022, discusses sentiment analysis of the implementation of an independent program to study at an independent campus with the Decision Tree, KNN and Naïve Bayes classification. Feature Extraction used in the study is Term Frequency and TF-IDF. The preprocessing stages of the study include case folding, tokenize, and stopword removal. Of the total 475 data taken, the data was then divided into two parts, namely test data and train data. The scale of data sharing is 80:20, where 20% of the total data is test data and the other 80% is train data with the Naïve Bayes accuracy value of 99.22%, while the KNN accuracy value is 96.90%, and the Decision Tree accuracy value is 37.21%.

2. RESEARCH METHODOLOGY

In this study, the system built was a sentiment analysis model from a review of practo applications using KNN and Word2Vec. The system built on this study is shown in Figure 1:

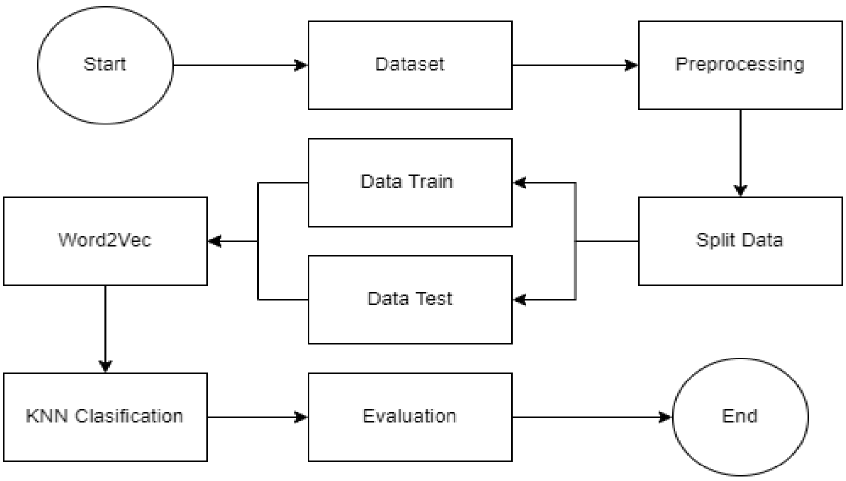

Figure 1. System Design Flow

2.1 Dataset

In this study, using a dataset of practo application reviews obtained from the Kaggle website. The data collected consisted of 7,156 practo app review data and the review data was in English.. This dataset does not include all reviews (there are about 250 thousand reviews in the appstore). This dataset has been labeled with the positive and negative classes shown in Figure 2. An example of the labeled dataset is shown in Table 1.

Table 1. Research Dataset

Label	Sentence
Positive	“Good app and available at all the times. Have made doctors available at some very critical times of emergency."

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Negative	"The 'medical records' feature is not smooth. When I select the option to upload photos from gallery, it does not show the content of galary rather it goes back to main window after few seconds.."

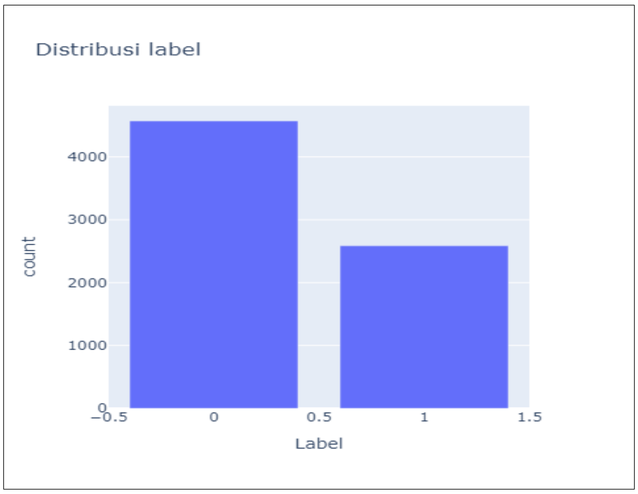

Figure 2. Label Distribution

2.2 Preprocessing

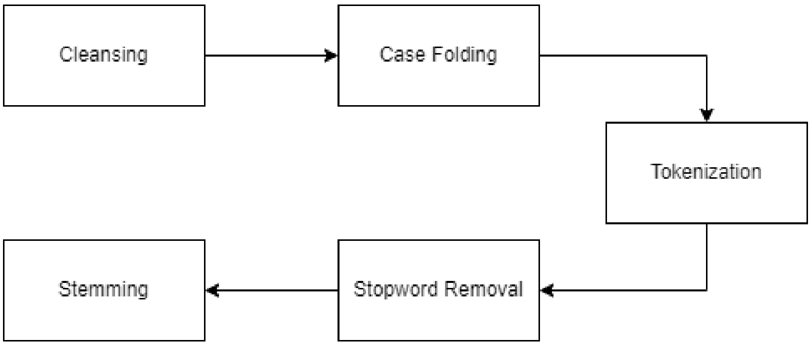

Figure 3. Preprocessing Stage

The preprocessing process begins after all the data has been collected and prepared. Preprocessing is done to fix data processing problems. The preprocessing stage carried out in this study is depicted in Figure 3. This study divides preprocessing into five processes, namely Cleansing, Stopword Removal, Case Folding, Stemming, and Tokenization. At the preprocessing stage, data in the review_type column is also changed. The change in data type changes the positive class to 1 and the negative class to 0.

2.2.1 Cleansing

Cleansing is the process of cleaning up attributes that are not needed in input data such as symbols and punctuation marks [10]. Table 2 is the result of the cleansing stage.

Table 2. Cleansing Result

Text	Cleansing Result
" Good app and available at all the times. Have made doctors available at some very critical times of emergency."	" Good app and available at all the times Have made doctors available at some very critical times of emergency"

2.2.2 Case Folding

During the case folding process, all characters in the data are converted into lowercase letters [13]. The results of case folding can be seen in Table 3.

Table 3. Case Folding Result

Cleansing Result	Case Folding Result
" Good app and available at all the times Have made doctors available at some very critical times of emergency "	" good app and available at all the times have made doctors available at some very critical times of emergency "

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2.2.3 Tokenization

Tokenization is divided by space and serves as a sentence breaker based on each word that composes it. [14]. Table 4 is the result of the tokenization stage.

Table 4. Tokenization Result

Case Folding Result	Tokenization Result
" good app and available at all the times have made doctors available at some very critical times of emergency "	"[good], [app], [and], [available], [at], [all], [the], [times], [have], [made], [doctors], [available], [at], [some], [very], [critical], [times], [of], [emergency]"

2.2.4 Stopword Removal

Stopword removal is removing meaningless words and unimportant words [15]. Table 5 is the result of the stopword removal stage.

Table 5. Stopword Removal Result

Tokenization Result	Stopword Removal Result
"[good], [app], [and], [available], [at], [all], [the], [times], [have], [made], [doctors], [available], [at], [some], [very], [critical], [times], [of], [emergency]"	"[good], [app], [available], [times], [made], [doctors], [available], [critical], [times], [emergency]"

2.2.5 Stemming

Turning words into root words is known as stemming. This process removes word affixes, namely suffixes, prefixes, and a combination of both [7]. Table 6 is the result of the stemming stage.

Table 6. Stemming Result

Stopword Removal Result	Stemming Result
"[good], [app], [available], [times], [made], [doctors], [available], [critical], [times], [emergency]"	"good app avail time made doctor avail critic time emerg"

After completing all stages of preprocessing, clean sentences shown in table 7.

Table 7. Preprocessing Stages Result

Text	Preprocessed Text
" Good app and available at all the times. Have made doctors available at some very critical times of emergency."	" good app avail time made doctor avail critic time emerg "

2.3 Split Data

After preprocessing is completed, the next step is to split the dataset. Data is divided or split into test and train data. In this analysis, the data is divided into 80% train data and 20% test data. After the data split is complete, the results can be shown in Table 8:

Table 8. Split Data Result

Split Data	Data Train	Data Test
Total Data	5724	1432
Positive	2063	910
Negative	3661	522

2.4 Word2Vec

After the preprocessing and split data stages are complete, the next step is to weight the words with Word2Vec. Word2Vec is a tool based on deep learning that aims to represent words in a context as a vector with N dimensions [6]. This research uses Word2vec as feature extraction. There are 2 types of Word2Vec models that can be used, the first type is the Continuous Bag of Words (CBOW) and the second type is Skip-Gram. The way CBOW works is to predict the context of words from previous words while the way Skip-gram works predicts the middle word context of the words to the left or right of a given word [9]. In this research, the model used is Skip-Gram. The use of Skip-Gram in this study is because Skip-Gram is an effective method for studying various vector representations of words available in unstructured text [6]. The equation used in the Skip-Gram model in number 1:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0}\log p(w_{t+j}|w_t) \tag{1}$$

Description:

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c = Training context measures
w_{t+j} = The word after the middle word
w_t = Center word
$p(w_{t+j}|w_t)$ = Word probability in the current word

Figure 4 shows the implementation of the above equations in the Skip-Gram model structure.

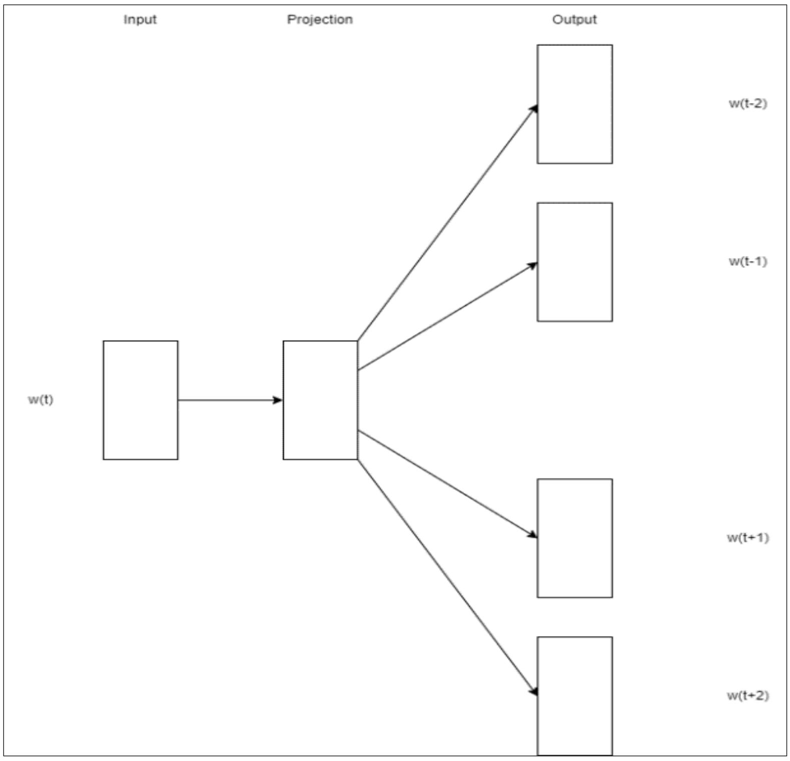

Figure 4. Skip-Gram Model [8]

2.5 K-Nearest Neighbor

After the feature extraction process using Word2Vec done, it is necessary to carry out the classification process. The classification used in this analysis is K-Nearest Neighbor. The K-Nearest Neighbor algorithm classifies new data based on the distance of the new data to some data or its closest neighbor [16]. The purpose of this algorithm is to use attributes and training samples to classify new objects [17]. The K-Nearest Neighbor classification is used because it has the advantages of being easy to understand, good performance, and easy to implement parameter tuning to adjust to research needs to achieve better results. [7]. K-Nearest Neighbor uses Euclidean distance to calculate the distance from one test data to all exercise data [18]. The euclidean distance formula can be seen at number 2:

$$D(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (2)$$

Description:
D : Distance between points
y : testing data
x : training data
K-Nearest Neighbor method can be calculated in the following way [17] :

a. Determine value of K.
b. Combine all train data to specify the new data distance. Distance is calculated using Euclidean distances.
c. Sort the distance from the closest.
d. Check the nearest neighbor's K class.
e. New class data = majority of the nearest neighboring K class specifies the K parameter.

2.7 Evaluation

In this study, the confusion matrix was used to conduct the evaluation process. The Confusion Matrix is used to find the value of several points needed for this stage such as precision, accuracy, F1-Score and recall [19]. The Confusion Matrix can be seen in Table 9:

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Table 9. Confusion Matrix

Confusion Matrix		Factual Value	
		Positive	Negative
Predicted Value	Positive	TP	FP
	Negative	FN	TN

Description:
TP = positive predicted and positive factual (true positive)
FN = negative predicted and positive factual (false negative)
FP = positive predicted and negative factual (false positive)
TN = negative predicted and negative factual (true negative)
To measure the performance of the classification process, precision, recall and f1-score are calculated. The formula for performance evaluation is as follows:
F1-Score is a weighted average by taking recall values and precision to calculate the performance of classification method [20]. Here is the formula for calculating F1-Score in number 3:

$$F1 - Score = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (3)$$

Precision is the comparison of the number of items correctly identified as positive with the number of items identified as positive [20]. Here is the formula for calculating Precision in number 4:

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

Recall or True Positive Rate (TPR) is a comparison of the number of relevant items correctly identified with all correct items [20]. Here is the formula for calculating Recall in number 5:

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

3. RESULT AND DISCUSSION

In this study, 7156 data were collected after the preprocessing process was successfully carried out. Then data division was carried out with a ratio of 80:20 and the results obtained were 5724 for training data and 1432 for test data. After the data is split, the next step is to perform feature extraction using Word2Vec. In feature extraction, each word will be implemented into a vector. After performing feature extraction, the next process is to perform classification using the K-Nearest Neighbor method. There are a total of 3 test scenarios conducted in this research. The first test scenario is by comparing the preprocessing stage using stemming and not using stemming. The purpose of the first scenario is to find out how the use of stemming in the preprocessing stage affects performance results. The second test scenario is to use dimension 100 and dimension 300 in Word2Vec feature extraction. The purpose of the second scenario is to find out how the selection of dimensions in Word2Vec feature extraction impacts the performance results. The third test scenario is to find the best K in the K-Nearest Neighbor method with a maximum limit of K ≤ 11. The purpose of scenario three is to find out whether the K value affects the performance of the KNN model.

Table 10. Experiment Scenario

Scenario	Experiment
1	Tests are carried out at the preprocessing stage to determine performance results using stemming and without using stemming.
2	Compare the use of Word2Vec feature extraction when using dimension 100 and dimension 300
3	Compare the use of k values in the KNN algorithm up to k ≤ 11

3.1 The Effect of Stemming

Tests are performed in the first scenario to find out if the stemming process in preprocessing affects the built model.. In this scenario, the preprocessing test is performed twice, using the stemming shown in figure 5 and not using the stemming shown in figure 6.

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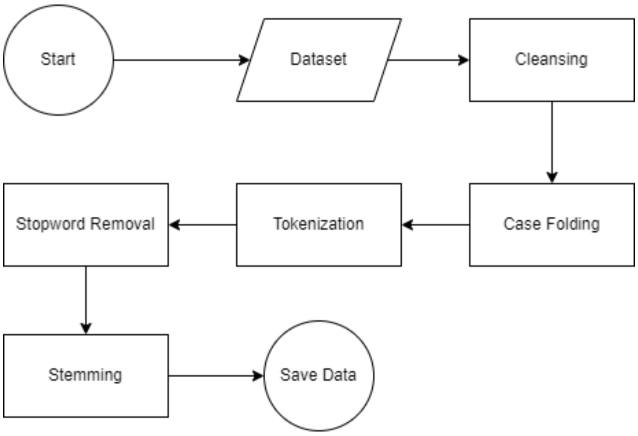

Figure 5. Preprocessing with stemming

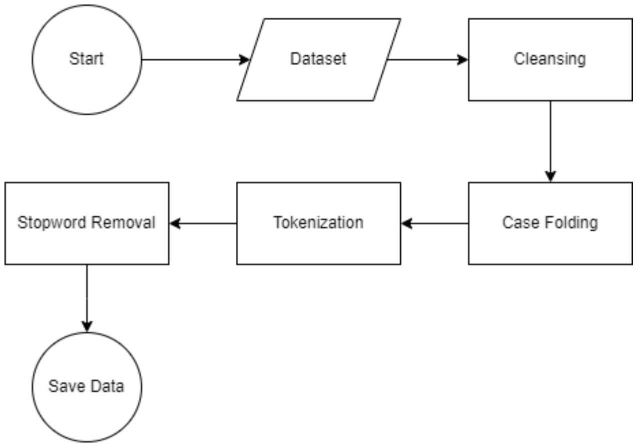

Figure 6. Preprocessing without stemming

Tests conducted using data with Word2Vec with a dimension of 300 and the K-Nearest Neighbor method. The following table 11 shows the test results from scenario 1:

Table 11. Scenario 1 Result

Preprocessing	Precission	Recall	F1-Score
With Stemming	**83.71%**	**73.92%**	**75.63%**
Without Stemming	83.65%	73.03%	74.68%

According to the test results shown in table 11 above, test are performed using stemming in preprocessing stage produce better precision, recall, and f1-score scores than Testing is carried out without the use of stemming at the preprocessing stage. Testing using stemming produces a precision of 83.71%, recall of 73.92%, and f1-score of 75.63% while testing without using stemming produces a precision of 83.65%, recall of 73.03%, and f1-score of 74.68%. Research [21] shows that stemming can improve model performance when used in the preprocessing stage. Model performance can be disrupted by features that are not very relevant to the KNN method. This shows that stemming is useful because it can reduce the number of features by cutting word affixes.

3.2 The Effect of Dimension on Word2Vec

In test scenario 2, tests were conducted to compare the impact of Word2Vec feature extraction with the KNN method. Testing is done by comparing the different dimensions in Word2Vec using data that has gone through the stemming process during preprocessing and the KNN method. The dimensions used are 100 and 300. The following Table 12 shows the test results from scenario 2.:

Table 12. Scenario 2 Result

Word2Vec Dimension	Precission	Recall	F1-Score
100	82.66%	72.24%	73.78%
300	**83.71%**	**73.92%**	**75.63%**

According to the test results shown in table 12 above, it show that test with 300 dimension on Word2Vec have better performance and stability than test with 100 dimension. This is because when the dimension is larger, there is

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more space to show the relationship between words. This richer representation of words can help find more relevant nearest neighbors when using the KNN method.

3.3 Find Best K in KNN

The third test scenario is to find best K in the K-Nearest Neighbor method with a maximum limit of K ≤ 11. In this scenario, the feature extraction used is Word2Vec with a dimension of 300 by involving stemming during preprocessing. Figure 7 show the statistic from scenario 3 and the test results of scenario 3 can be seen in Table 13 below:

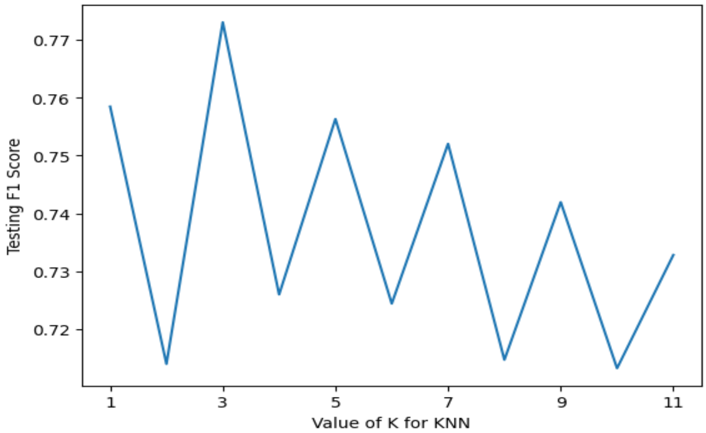

Figure 7. Statistical Diagram Scenario 3

Table 13. Scenario 3 Result

K Value	F1-Score
1	75.84%
2	71.40%
3	77.30%
4	72.60%
5	75.63%
6	72.44%
7	75.20%
8	71.47%
9	74.19%
10	71.32%
11	73.28%

According to the test results shown in Figure 7 and Table 13 above, it shows that the highest f1-score value is obtained at K = 3 with an f1-score value of 77.30% while the lowest f1-score value is obtained at K = 10 with an f1-score value of 71.32%. The graph above shows that using a smaller K value can produce a better f1-score than using a larger K value, this is shown in the graph above which tends to decrease when using a larger K value. In this study, it can be concluded that the K value can affect the results of the performance of the K-Nearest Neighbor model.

4. CONCLUSION

Based on the results of this study, a system can be built about Sentiment Analysis of Practo Application Reviews Using KNN and Word2Vec Methods, with the first test scenario comparing performance results when using stemming and not using stemming in the preprocessing process, the second test scenario comparing Word2Vec feature extraction when using dimension 100 and dimension 300, the third test scenario finding the best K value for the K-Nearest Neighbor method with a maximum limit of K value ≤ 11. Based on the results of the scenario tests that have been carried out, it can be concluded that the use of stemming during the preprocessing process can affect the performance of the results, these results can be proven in the first test scenario where the performance when using stemming gets better recall, precision, and f1-score values than without using stemming. In the second test scenario, it can be concluded that dimensional differences in Word2Vec feature extraction can affect performance results where when using dimension 300, the recall, precision, and f1-score values are better than using dimension 100. The third test scenario proves that the K value can affect the results on the performance of the KNN model, the K = 3 value gets the best result with an f1-score of 77.30% compared to other K values with a maximum value of K ≤ 11. Suggestions for further research are to replace stemming with lemmatization in the preprocessing process, combine other feature extractions to get varied performance results, compare more K values to get more diverse results.

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