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Text Classification Using TF-IDF and Naïve Bayes: Case Study of MyXL App User Review Data

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ABSTRACT

The MyXL application, developed by leading Indonesian operator XL Axiata, allows customers to independently manage their telecommunication services. However, a significant volume of negative user reviews necessitates a deeper analysis of user sentiment. This research classifies MyXL app reviews using the TF-IDF (Term Frequency-Inverse Document Frequency) method for feature extraction and the Naïve Bayes algorithm for sentiment classification, implemented via a Python-based GUI. The study's objective is to categorize reviews into positive, negative, and neutral sentiments. A dataset of 1000 user reviews from Kaggle underwent comprehensive preprocessing—including text cleaning, normalization, tokenization, stopword removal, and stemming—before conversion into a numerical representation using TF-IDF. The classification model, built with the Naïve Bayes algorithm, was evaluated using accuracy, precision, recall, and F1-score metrics. The model achieved an accuracy of 61.5%. This finding demonstrates that combining TF-IDF and Naïve Bayes is effective for classifying sentiment in Indonesian text reviews, particularly within the mobile app domain. Furthermore, the methodology shows clear potential for development into a large-scale and automated user opinion analysis system.

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1. INTRODUCTION

The advancement of information technology and the increasing use of mobile applications like MyXL have generated a large volume of unstructured user reviews. These reviews contain valuable information regarding user satisfaction and dissatisfaction with the application. However, manual analysis of this review data is highly inefficient, thus requiring automated techniques such as text classification. TF-IDF is a popular and effective feature extraction method for text representation, while Naïve Bayes is a classic algorithm with strong performance in classifying Indonesian-language text. User reviews serve as an indicator for assessing the quality of an application and user satisfaction. However, with the enormous volume of review data, it is crucial to have an efficient method for analyzing and categorizing the sentiment contained within these reviews [1]. Sentiment classification is an essential process that allows for a better understanding of public opinion regarding a product or service. One widely used method in text classification is Naïve Bayes, which is known for its simplicity and its ability to handle large datasets [2].

One method that can be used in the sentiment classification process is TF-IDF, which functions as a feature extraction technique. By using TF-IDF, each word in a user review is assigned a weight according to its relevance within the document and the entire document collection, enabling researchers to better identify sentiment. Furthermore, by developing a GUI-based application, user interaction with the data can become more intuitive [3]. A GUI allows users to perform analysis with an easy-to-use application and provides real-time visualization of the obtained results. Based on a literature review, there is a consistent methodology in sentiment analysis research that utilizes the Naïve Bayes algorithm. Most studies apply the TF-IDF method for feature extraction following a comprehensive data preprocessing stage, which includes case folding, cleansing, tokenizing, and stemming [4, 5]. Research data is gathered from various online sources such as film reviews on IMDb [4], comments on YouTube [6, 7], product reviews on Shopee [5] and Female Daily [8, 9], user feedback on Tiket.com [10], as well as app reviews on the Google Play Store [11] and posts on Twitter [12]. Some studies also implement additional techniques like Laplace Smoothing to improve classification performance [4], N-Gram variations for feature extraction [12], and upsampling to handle imbalanced data [10].

The results from applying this methodology show varying levels of accuracy. Several studies achieve exceptionally high accuracy, such as 98.19% in the sentiment analysis of bullying cases [6] and 96% for comments on public policy [7], while others fall within the 80-89% range [4, 5, 9, 13]. Nevertheless, some studies note a relatively low F1-Score or precision despite high accuracy [8, 10]. The primary strengths often highlighted are the use of large and balanced datasets [4], complete metric evaluations [9], and analysis of relevant real-world data [6, 5]. However, common weaknesses include a reliance on a single algorithm without comparison [4, 6], the use of small or imbalanced datasets [10, 9], a lack of detail in the preprocessing stage or class distribution [6, 7], and an analytical scope limited to a single product or specific topic [9, 12].

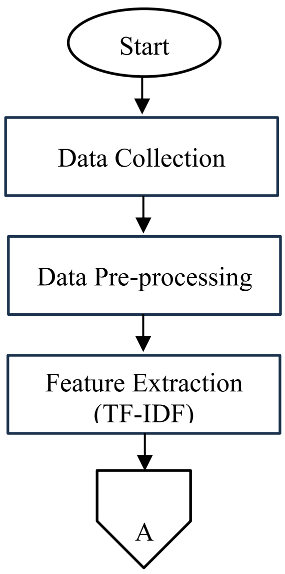
The foundation of this research is text classification, which is the process of categorizing documents to determine positive, negative, or neutral sentiment [14]. This process is supported by feature extraction methods like TF-IDF (Term Frequency-Inverse Document Frequency) to assess the relevance of words within a document [15, 16], as well as probabilistic classification algorithms like Naïve Bayes, which is effective despite its assumption of feature independence [17]. The context for applying these methods is the MyXL application from XL Axiata, which is designed to simplify customer service management [18, 19]. Previous research has examined the user satisfaction levels for this application [18], highlighted the analytical challenges posed by imbalanced review data [19], and assessed its competitive position [20]. Consequently, applying text classification to MyXL reviews is relevant for efficiently evaluating user sentiment on a large scale [21], with results that can be utilized by developers for future service enhancements [22].

This research aims to build a sentiment classification model by utilizing TF-IDF as the feature extraction method and Naïve Bayes as the classification algorithm, and to measure its performance using accuracy, precision, recall, and F1-score metrics. The findings of this study are expected to provide useful recommendations for application developers in creating more effective sentiment analysis systems in the future, as well as to contribute academically to the application of text classification methodologies for mobile app reviews. Thus, this study seeks to answer how the Naïve Bayes algorithm performs in classifying the sentiment of MyXL app user reviews after text features are processed with TF-IDF, while also exploring the potential for developing a GUI-based interface to make user interaction with the analysis system more intuitive and informative.

2. METHOD

2.1. Research Design

This study uses a quantitative approach with a text classification experiment in the figure 1.



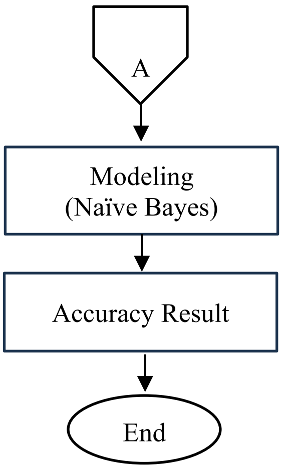


Figure 1. Research flow

2.2. Data Collection

The dataset was obtained from https://www.kaggle.com/datasets/dimasdiandraa/data-ulasan-terlabel?resource=download, which contains user review data for the MyXL application, gathered through web scraping techniques from the Google Play Store over a specific period. The dataset consists of 1000 text reviews that have been labeled by Dra. Umi Kolisoh, M.Pd, Widi, and Nanda into positive, negative, and neutral sentiment categories.

2.3. Data Preprocessing

a. Cleaning
   In this stage, data is cleaned by removing unimportant or disruptive characters from the text, such as symbols, emojis, and links within the review data, making it cleaner and easier to process.
b. Case Folding
   This stage involves standardizing the letters by converting them all to lowercase to prevent word duplication due to differences in capitalization.
c. Normalization
   Normalization is the process of converting non-standard words, such as slang or abbreviations, into their standard form according to the official Indonesian dictionary (Kamus Besar Bahasa Indonesia - KBBI).
d. Tokenization
   This stage involves breaking down sentences or paragraphs into individual word units (called tokens) to facilitate further analysis.
e. Stopword Removal
   This involves removing common words (stopwords) that appear frequently but do not provide significant information, such as: “yang” (which/that), “adalah” (is), “itu” (that), “dan” (and), “ke” (to), “dengan” (with), etc.
f. Stemming
   This process reduces derived words to their base or root form (stem) to ensure a more general and uniform word representation.

2.3. Feature Extraction

The TF-IDF method is used to convert text into a numerical representation that reflects the importance of a word within a document and across the entire collection of documents.

2.4. Classification

Naïve Bayes, specifically Multinomial Naïve Bayes, was chosen for the classification of the review data. The model was trained using training data and tested on testing data with an 80:20 split.

2.5. Model Evaluation

The evaluation method uses a confusion matrix to calculate accuracy, precision, recall, and F1-Score.

3. RESULTS AND DISCUSSION

3.1. Data Collection

The dataset used in this research is a collection of user reviews for the MyXL application, containing a total of 1,000 rows of data, each representing a single user review of the MyXL app. The data can be seen in the following figure.

userName	score	at	Ulasan	Sentimen Widi	Sentimen Nanda	Sentimen Dra. UMI KOLISOH, M.Pd	Sentimen	Keterangan:
Deden Herdiana	4	2022-02-11 8:42:00	Harusnya dikasih bintang 4 bilang terimakasih....	1	1	1	-1	1. negatif
Herry Ghunawan	1	2022-02-11 7:53:00	Tolong dong masalah jaringan hampir setiap har...	1	1	1	-1	2. positif
Miyuki	5	2022-02-11 5:50:00	Saya mau komen lagi,miminnnn kenapa akhir akhi...	1	1	1	-1	3. netral
Wildan Saat Almaarif	2	2022-02-11 5:33:00	Bonus kouta tiktok 13gb tidak diaktifkan/tidak...	1	1	1	-1	NaN
putri purwantiy	3	2022-02-11 3:10:00	Sejauh ini bagusÂ² aja sih apk nya, tpi udh bb...	3	3	3	0	NaN

Figure 2. Data collection

3.2. Text Processing

a. Cleaning

The following is the result after the data cleaning process, which involved removing unimportant or disruptive characters from the text, such as symbols, emojis, and links, to make the review data cleaner and easier to process.

	Ulasan	cleaning
0	Harusnya dikasih bintang 4 bilang terimakasih....	Harusnya dikasih bintang bilang terimakasih B...
1	Tolong dong masalah jaringan hampir setiap har...	Tolong dong masalah jaringan hampir setiap har...
2	Saya mau komen lagi,miminnnn kenapa akhir akhi...	Saya mau komen lagimiminnnn kenapa akhir akhir...
3	Bonus kouta tiktok 13gb tidak diaktifkan/tidak...	Bonus kouta tiktok gb tidak diaktifkantidak di...
4	Sejauh ini bagusÂ² aja sih apk nya, tpi udh bb...	Sejauh ini bagus aja sih apk nya tpi udh bbrp ...

Figure 3. Cleaning process

b. Case Folding

In this process, all letters were converted to lowercase to prevent word duplication due to differences in capitalization.

cleaning	case_folding
Harusnya dikasih bintang bilang terimakasih B...	harusnya dikasih bintang bilang terimakasih b...
Tolong dong masalah jaringan hampir setiap har...	tolong dong masalah jaringan hampir setiap har...
Saya mau komen lagimiminnnn kenapa akhir akhir...	saya mau komen lagimiminnnn kenapa akhir akhir...
Bonus kouta tiktok gb tidak diaktifkantidak di...	bonus kouta tiktok gb tidak diaktifkantidak di...
Sejauh ini bagus aja sih apk nya tpi udh bbrp ...	sejauh ini bagus aja sih apk nya tpi udh bbrp ...

Figure 4. Case folding process

c. Normalization

N Normalization was performed to convert non-standard words, such as slang or abbreviations, into their standard form according to the KBBI (Great Dictionary of the Indonesian Language). The dictionary was obtained from a public GitHub repository: https://github.com/analysisdatasentiment/kamus_kata_baku/raw/main/kamuskatabaku.xlsx. The results can be seen in the following figure.

case_folding	normalisasi
harusnya dikasih bintang bilang terimakasih b...	harusnya dikasih bintang bilang terimakasih be...
tolong dong masalah jaringan hampir setiap har...	tolong dong masalah jaringan hampir setiap har...
saya mau komen lagimiminnnn kenapa akhir akhir...	saya mau komen lagimiminnnn kenapa akhir akhir...
bonus kouta tiktok gb tidak diaktifkantidak di...	bonus kouta tiktok gb tidak diaktifkantidak di...
sejauh ini bagus aja sih apk nya tpi udh bbrp ...	sejauh ini bagus saja sih apk ya tapi sudah be...

Figure 5. Normalization process

d. Tokenization
This stage involves splitting sentences or paragraphs into word units (called tokens) to facilitate further analysis.

case_folding	normalisasi	tokenize
harusnya dikasih bintang bilang terimakasih b...	harusnya dikasih bintang bilang terimakasih be...	[harusnya, dikasih, bintang, bilang, terimakas...
tolong dong masalah jaringan hampir setiap har...	tolong dong masalah jaringan hampir setiap har...	[tolong, dong, masalah, jaringan, hampir, seti...
saya mau komen lagimiminnnn kenapa akhir akhir...	saya mau komen lagimiminnnn kenapa akhir akhir...	[saya, mau, komen, lagimiminnnn, kenapa, akhir...
bonus kouta tiktok gb tidak diaktifkantidak di...	bonus kouta tiktok gb tidak diaktifkantidak di...	[bonus, kouta, tiktok, gb, tidak, diaktifkanti...
sejauh ini bagus aja sih apk nya tpi udh bbrp ...	sejauh ini bagus saja sih apk ya tapi sudah be...	[sejauh, ini, bagus, saja, sih, apk, ya, tapi,...

Figure 6. Tokenization process

e. Stopword Removal
This step removes common words (stopwords) that appear frequently but do not provide significant information, such as: “yang” (which/that), “adalah” (is), “itu” (that), “dan” (and), “ke” (to), “dengan” (with), etc.

normalisasi	tokenize	stopword removal
harusnya dikasih bintang bilang terimakasih be...	[harusnya, dikasih, bintang, bilang, terimakas...	[dikasih, bintang, bilang, terimakasih, mengas...
tolong dong masalah jaringan hampir setiap har...	[tolong, dong, masalah, jaringan, hampir, seti...	[tolong, jaringan, leg, parah, kecewa, costumer]
saya mau komen lagimiminnnn kenapa akhir akhir...	[saya, mau, komen, lagimiminnnn, kenapa, akhir...	[komen, lagimiminnnn, jaringan, xl, parah, pas...
bonus kouta tiktok gb tidak diaktifkantidak di...	[bonus, kouta, tiktok, gb, tidak, diaktifkanti...	[bonus, kouta, tiktok, gb, diaktifkantidak, sa...
sejauh ini bagus saja sih apk ya tapi sudah be...	[sejauh, ini, bagus, saja, sih, apk, ya, tapi,...	[bagus, sih, apk, ya, sinyal, xl, hilang, isi,...

Figure 7. Stopword removal process

f. Stemming
This process involves converting derived words into their base or root form (stem) to create a more general and uniform word representation.

tokenize	stopword removal	steming_data
[harusnya, dikasih, bintang, bilang, terimakas...	[dikasih, bintang, bilang, terimakasih, mengas...	kasih bintang bilang terimakasih asih bintang ...
[tolong, dong, masalah, jaringan, hampir, seti...	[tolong, jaringan, leg, parah, kecewa, costumer]	tolong jaring leg parah kecewa costumer
[saya, mau, komen, lagimiminnnn, kenapa, akhir...	[komen, lagimiminnnn, jaringan, xl, parah, pas...	komen lagimiminnnn jaring xl parah pas searchi...
[bonus, kouta, tiktok, gb, tidak, diaktifkanti...	[bonus, kouta, tiktok, gb, diaktifkantidak, sa...	bonus kouta tiktok gb diaktifkantidak sayajadi...
[sejauh, ini, bagus, saja, sih, apk, ya, tapi,...	[bagus, sih, apk, ya, sinyal, xl, hilang, isi,...	bagus sih apk ya sinyal xl hilang isi pulsa to...

Figure 8. Stemming process

g. Labeling
The label distribution across the 1,000 data points shows a data imbalance in each sentiment class. The negative class is the majority class with 613 data points, the neutral class has 226 data points, and the positive class has 161 data points, as can be seen in the following diagram.

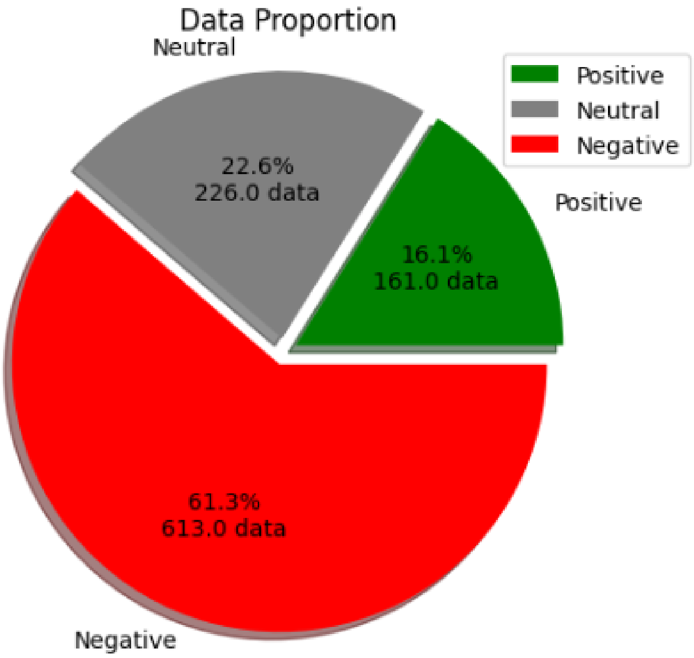


Figure 9. Labeling

3.3. Feature Extraction

In this process, a total of 4,504 unique words were identified, which can be seen in the following figure.

```
Index(['score', 'at', 'Ulasan', 'Sentimen Widi', 'Sentimen Nanda',
       'Sentimen Dra. UMI KOLISOH, M.Pd', 'Sentimen', 'Keterangan:'],
      dtype='object')
Jumlah kata unik: 4504

[ ] term_fit.vocabulary_

{'harusnya': 1595,
 'dikasih': 1158,
 'bintang': 770,
 'bilang': 765,
 'terimakasih': 4100,
 'belum': 622,
 'mau': 2472,
 'ngasih': 2866,
 'soalnya': 3890,
 'jaringan': 1761,
 'di': 1075,
 'area': 426,
```

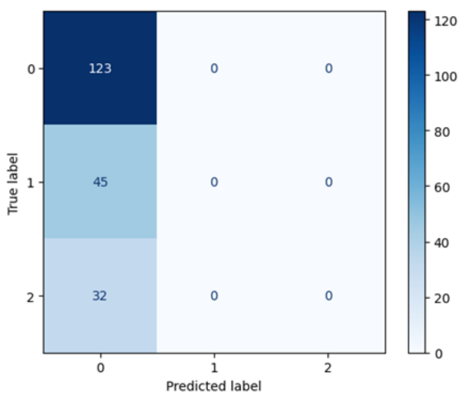
Figure 10. Feature extraction

3.4. Classification Results

The results from the confusion matrix show that:

a. Class -1 (negative) had 123 data points that were correctly predicted (True Negative) out of a total of 123, indicating a high recall of 1.00 for this class.
b. Class 0 (neutral) was not successfully predicted at all; all neutral data (45 data points) were incorrectly classified into the negative class.
c. Class 1 (positive) was also not predicted correctly; all 32 positive data points were classified into the negative class.

Overall, the model is biased towards the negative class (-1), resulting in precision and recall values of 0 for the neutral and positive classes. This caused the macro average precision to be only 0.20 and the macro average f1-score to be 0.25. The accuracy score obtained on the test data was 61.5%, which is attributed to the highly imbalanced data (the majority being the negative class).




```
Confusion Matrix:
 [[123   0   0]
 [ 45   0   0]
 [ 32   0   0]]
Naive Bayes:
Training Accuracy: 0.6175
Test Accuracy: 0.615
              precision    recall  f1-score   support

          -1       0.61      1.00      0.76       123
           0       0.00      0.00      0.00        45
           1       0.00      0.00      0.00        32

    accuracy                           0.61       200
   macro avg       0.20      0.33      0.25       200
weighted avg       0.38      0.61      0.47       200
```

Figure 11. Classification result

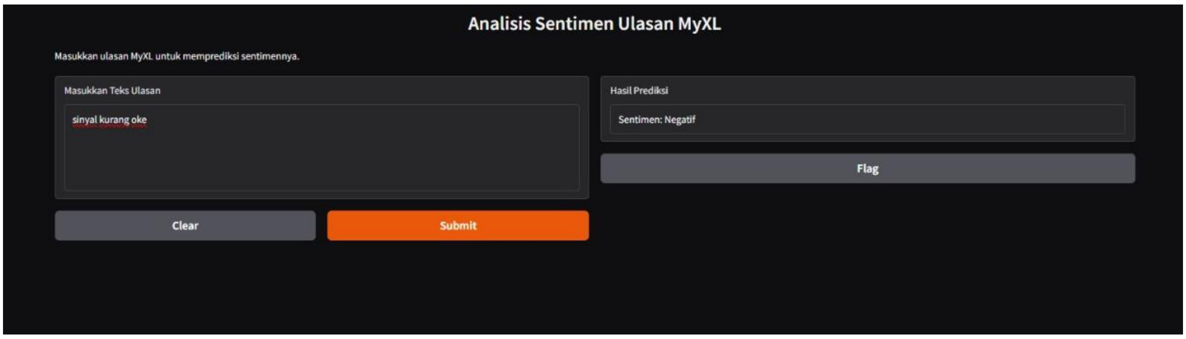


Figure 12. Implementation was done using a Python-based GUI.

4. CONCLUSION

Based on the research findings and the implementation of the Naïve Bayes algorithm on the MyXL application review data, the TF-IDF method for feature extraction proved capable of capturing important text representations. The developed model showed a classification accuracy of 61.5%; this is because the negative sentiment class was larger than the positive and neutral sentiment classes. This accuracy score indicates that there is still potential to improve the model's performance, especially in distinguishing between neutral and negative sentiments, which have contextual similarities. The use of a Python-based GUI also successfully simplified the visualization of results and enhanced the user experience in analyzing the review data. Thus, the combination of TF-IDF and Naïve Bayes can serve as an initial foundation for building a lightweight and widely implementable automated text classification system. Future research could test data balancing techniques like SMOTE to address the imbalanced class distribution to improve classification performance and compare it with other algorithms such as Support Vector Machine (SVM) or Random Forest.

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