Jurnal Teknik Informatika (JUTIF) Vol. 6, No. 4, August 2025, Page. 1861-1880
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4875

Sentiment Analysis of Fizzo Novel Application Using Support Vector Machine and Naïve Bayes Algorithm with SEMMA Framework

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Received : Jun 13, 2025; Revised : Jul 7, 2025; Accepted : Jul 10, 2025; Published : Aug 18, 2025

Abstract

The increasing popularity of digital reading platforms in Indonesia, such as Fizzo Novel, has generated many user reviews that can be analyzed to understand their satisfaction. This study analyzes user sentiment toward Fizzo Novel using the SEMMA (Sample, Explore, Modify, Model, Assess) framework, and compares the performance of the Support Vector Machine (SVM) and Naïve Bayes algorithms. A total of 139,759 reviews were collected from the Google Play Store through web scraping. The data was then processed through normalization, tokenization, lexicon-based sentiment labeling, and feature extraction using TF-IDF. To address class imbalance, the SMOTE technique was applied. The results showed that SVM achieved the highest accuracy, exceeding 96%, with a consistent F1-score across all sentiment classes. In contrast, Naïve Bayes recorded lower accuracy (75.82% before SMOTE and 73.63% after SMOTE), along with a decline in performance for the neutral class. SVM proved more reliable in handling large and imbalanced text data. Practically, the results of this study can help application developers such as Fizzo Novel in automatically understanding user opinions. With an accurate sentiment classification model, developers can monitor reviews in real-time, identify issues such as excessive advertising or an unpopular chapter division system, and design feature improvements based on real user needs. This research also provides a foundation for algorithm selection in future large-scale sentiment analysis projects and recommends SVM as the more appropriate choice in this context.

Keywords : *Naïve Bayes, SEMMA, Sentiment Analysis, SMOTE, Support Vector Machine, TF-IDF.*

1. INTRODUCTION

Technological developments have spread throughout the world, including Indonesia, which is also affected by these advances. This technological development is very rapid and difficult to control [1]. With widespread internet penetration and increasing adoption of smart devices, Indonesians are now increasingly encouraged to utilize various digital applications in their daily lives [2]. This digital transformation has not only penetrated the industrial sector and public services, but has also changed the way individuals access entertainment and information [3], including reading.

In recent years, reading practices have undergone significant changes [4]. While reading novels used to be synonymous with print media such as physical books, the activity has now moved to digital platforms. Online reading applications, especially those that provide fiction stories, have become a popular alternative that offers ease of access, diversity of content, and a more dynamic interactive experience [5]. This change shifts the paradigm of modern literacy from conventional to technology based.

One of the most notable apps in this category is Fizzo Novel. This app offers a variety of story genres, both local and international, and utilizes monetization mechanisms such as paid features and a reader reward system. By early 2025, Fizzo Novel had been downloaded over 50 million times and

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received over 1 million user reviews on the Google Play Store, making it one of the fastest-growing digital reading apps in Southeast Asia [6]. This popularity makes Fizzo Novel a relevant subject for analysis, particularly from the perspective of user satisfaction and perception. The large volume of user reviews available serves as a valuable data source for analyzing trends in opinions and feedback regarding the app [7]. Additionally, the impact of the monetization mechanisms implemented on the overall user experience must also be considered [8].

Sentiment analysis is a technique in the field of data mining and natural language processing (NLP) used to identify and classify opinions or emotions contained in a text [9]. In a business context, sentiment analysis serves as a strategic tool to understand customer needs, evaluate service satisfaction, as well as support data-driven decision making [10]. In this research, two popular algorithms for sentiment classification are used, namely Support Vector Machine (SVM) and Naïve Bayes. Both have been widely applied in various sentiment analysis studies due to their effectiveness in classifying positive and negative opinions from review text [11].

Research related to sentiment analysis of the Fizzo Novel application has been conducted and shows that although this application is popular as a digital reading platform among the younger generation, there are various reviews from its users, both positive and negative. To dig deeper into user opinions, a sentiment analysis was conducted on 90.936 user reviews on the Google Play Store using the Naïve Bayes algorithm. The classification results show that 80.162 reviews fall into the positive category and 10.774 reviews are negative. The classification process through pre-processing, TF-IDF, and confusion matrix stages resulted in an accuracy of 83%, precision 85%, recall 82%, and F1-score of 83%, indicating that the Naïve Bayes algorithm is quite effective in classifying user sentiment towards the Fizzo Novel application [6]. Although the results were quite good, the study only used one algorithm and did not apply a more systematic analytical approach such as the SEMMA framework.

Sentiment analysis of public opinion regarding Covid-19 vaccination has been carried out in previous studies. This research utilizes 5.000 tweet data from the Twitter platform. To classify the data, two methods were used, namely Support Vector Machine (SVM) and Naïve Bayes (NB). The classification process is carried out with various kernels in the Support Vector Machine (SVM), including linear, polynomial, and RBF. The results show that the RBF kernel in SVM gives the highest accuracy of 88.8%, outperforming Naïve Bayes (NB) which gives an accuracy of 82.51%. This shows that the SVM method with RBF kernel is superior in classifying public sentiment towards the Covid-19 vaccination policy on Twitter [12].

Sentiment analysis has been used in previous studies to understand people's opinions towards online dating apps such as Tinder. In this study, Naïve Bayes and Support Vector Machine algorithms were used to classify the sentiment of 2.787 user reviews collected from Google Play Store. After optimization using the SMOTE technique to balance the data, the test results showed that the Support Vector Machine algorithm achieved 85% accuracy, while Naïve Bayes achieved 84% accuracy. Both models performed reasonably well in recognizing positive and negative sentiments, but SVM appeared slightly more stable. This finding is consistent with previous research that shows the superiority of SVM in sentiment classification, especially in the context of digital applications that have a large volume of diverse reviews [13].

From the literature review presented, it can be identified that there are research gaps that have not been explored much. First, there are still few studies that use the SEMMA framework comprehensively and systematically in sentiment analysis of digital reading applications. Second, there are not many studies that directly compare the performance of Support Vector Machine (SVM) and Naïve Bayes algorithms on large and unbalanced user review datasets, such as those found in the Fizzo Novel app. Third, most previous studies have not explicitly utilized sentiment analysis results as a basis for providing practical input to developers in designing service improvement strategies based on user

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opinions. Therefore, this study aims to analyze user sentiment in Fizzo Novel app reviews using the SEMMA framework, while comparing the performance of SVM and Naïve Bayes algorithms in sentiment classification to understand user perceptions and provide strategic recommendations for future app development.

2. METHOD

This research uses the SEMMA (Sample, Explore, Modify, Model, Assess) method approach as the main framework in the sentiment analysis classification process. SEMMA was developed by the SAS Institute and designed to support systematic and structured data mining processes [14]. In the context of this research, the SEMMA framework is used to analyze the sentiment contained in user reviews of the Fizzo Novel application taken from the Google Play Store. Each stage in SEMMA has an important role in ensuring that the data used is analyzed correctly and produces an optimal classification model [15]. Figure 1 is a flow of research stages

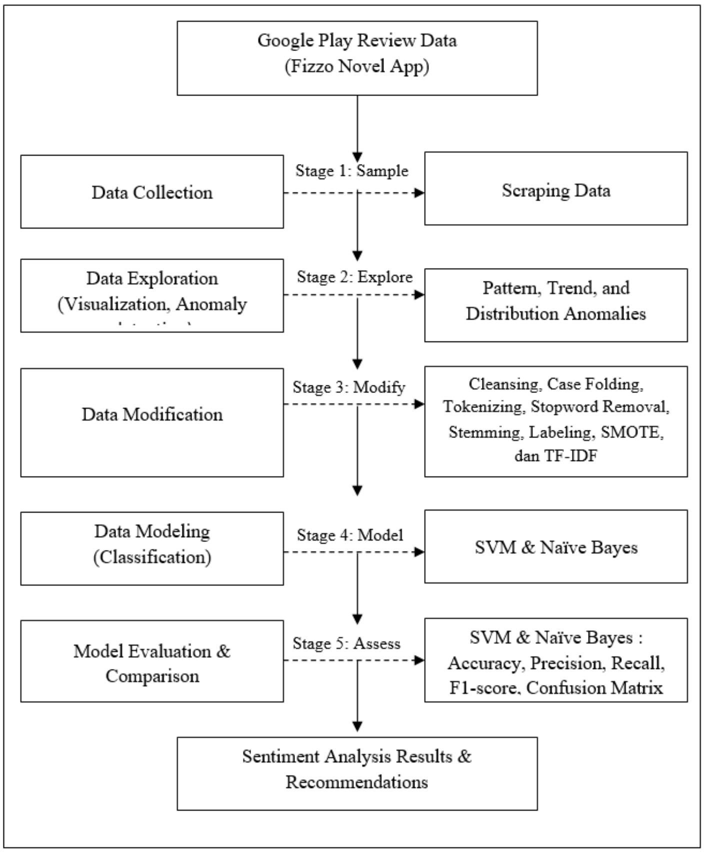

Figure 1. Research Stages

2.1. Sample

The first stage in SEMMA is Sample [16]. At this stage, user review data for the Fizzo Novel application is automatically collected from the Google Play Store platform using web scraping techniques. The web scraper used is designed to extract important information such as review content, star rating, and publication date. The data is collected in Comma Separated Value (CSV) file format for further exploration.

2.2. Explore

The next stage in SEMMA is explore. The explore stage aims to understand the characteristics of the data through visualization and descriptive statistical analysis [17]. In this stage, patterns, trends, distributions, and anomalies in the data are identified. A deep understanding of the data will help in making decisions regarding preprocessing, feature selection, and modeling.

2.3. Modify

The Modify stage is an important process in data preparation before modeling. In this stage, text data preprocessing is carried out to ensure that the data is in a clean and consistent format so that it can be processed by the classification algorithm optimally. In addition, this stage also includes the application of the SMOTE (Synthetic Minority Oversampling Technique) technique which is used to handle class imbalance between reviews with positive and negative sentiments, so that the model is not biased towards the majority class and is able to make more accurate predictions [18].

2.3.1. Data Preprocessing

The preprocessing stage is a very important first step in the text-based sentiment analysis process. Raw data obtained from social media, such as user reviews on Google Play Store, are generally unstructured and contain various non-informative elements such as symbols, emoticons, and unimportant words. Therefore, a series of preprocessing processes such as cleansing, case folding, tokenizing, stopword removal, stemming and labeling are carried out to clean and standardize the data so that it is ready for analysis. preprocessing aims to convert data into a more uniform base word form and can be processed by machine learning models optimally, so as to increase the accuracy of sentiment analysis generated [19].

2.3.2. Feature Extraction

In feature extraction, text representation is done using the TF-IDF (Term Frequency-Inverse Document Frequency) technique, which is a weighting method used to represent text in numerical form so that it can be processed by machine learning algorithms [20]. This technique measures how important a word (term) is in a document (document) relative to the entire set of documents (corpus). The main component of TF-IDF consists of two parts, namely Term Frequency (TF) which calculates the frequency of occurrence of a term in a document, and Inverse Document Frequency (IDF) which assesses how rarely the term appears in all documents. The formulas used in the TF-IDF process are shown in equations 1, 2, and 3 :

- Term Frequency (TF):

$$\mathrm{TF}\ (\mathrm{t},\mathrm{d}) = \frac{\text{Jumlah kemunculan term t dalam dokumen } d}{\text{Total jumlah term dalam dokumen } d} \tag{1}$$

- Inverse Document Frequency (IDF):

$$\mathrm{IDF}\ (\mathrm{t},\mathrm{D}) = log\left(\frac{N}{DF(t)} + 1\right) \tag{2}$$

- TF-IDF:

$$TF - IDF\ (t, d, D) = TF(t, d)\ \mathrm{X}\ IDF\ (t, D) \tag{3}$$

2.3.3. Synthetic Minority Oversampling Technique (SMOTE)

In sentiment analysis classification, class imbalance is a common problem that can affect the performance of machine learning models. To address this, the Synthetic Minority Oversampling Technique (SMOTE) is used as an oversampling method by creating synthetic data from minority classes. SMOTE works by finding the nearest neighbor of the minority sample and creating a new sample between them using vector interpolation, so that the class distribution becomes more balanced and the model can learn more fairly without bias towards the majority class [21]. the application of SMOTE is proven effective in significantly improving accuracy, precision, and recall in classification models [22].

2.4. Model

Furthermore, to analyze sentiment reviews on the Fizzo Novel application, two classification algorithm models are used, namely Support Vector Machine (SVM) and Naïve Bayes.

2.4.1. Support Vector Machine (SVM)

Support Vector Machine (SVM) is an algorithm that works by finding the optimal hyperplane to maximize the separation of two classes of data. One of the advantages of SVM is its ability to handle high-dimensional data such as text. In its implementation, kernel parameters greatly determine the performance of the model. This study uses a linear kernel, as it is suitable for text data and provides stable results while being computationally efficient [23]. Other kernels, such as polynomial or RBF, can be used, but the linear kernel is superior in cases of linearly separable data, such as TF-IDF representations.

2.4.2. Naïve Bayes

Naïve Bayes is a classification algorithm based on Bayes' theorem with the assumption of independence between features. It calculates the probability of a data belonging to a particular class based on the frequency of occurrence of features in the training data. Despite its simplicity, Naïve Bayes has proven to be effective in various text classification tasks, including sentiment analysis. Previous research shows that the use of Naïve Bayes in sentiment analysis of public opinion on the Job Creation Law on Twitter is able to produce an accuracy of 89.9% and a balanced f1-score, making it a reliable method in classifying positive and negative opinions [24].
The Naive Bayes Theorem formula is shown in equation 4 below:

$$P(H|X) = \frac{P(X|H)}{P(X)}.P(H) \tag{4}$$

Dimana:
X : Data with unknown class
H : Hypothesize that data X belongs to a certain class
P(H|X) : Probability that hypothesis H is true based on data X (posterior probability)
P(H) : Prior probability of hypothesis H before seeing data X
P(X|H) : Probability of getting data X if hypothesis H is true (likelihood)
P(X) : Overall probability of the data X

2.5. Assess

The Assess stage is the last step in the SEMMA framework which focuses on evaluating the performance of the classification model that has been built. Evaluation is carried out using metrics such as accuracy, precision, recall, and F1-score, each of which provides an overview of the accuracy and completeness of model predictions. In this research, the evaluation aims to compare the performance of

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Support Vector Machine (SVM) and Naïve Bayes algorithms in classifying positive and negative sentiments from user reviews. Confusion matrix is used as the basis for the calculation of these metrics to determine the most superior model in analyzing sentiment towards the Fizzo Novel application [25].

3. RESULT

3.1. Sample

The first stage in the SEMMA framework is Sample, which focuses on collecting and selecting initial data that will be used to build sentiment classification models. In this study, the dataset used is a collection of reviews from users of the Fizzo Novel application originating from the Google Play Store platform. The data collection process is carried out automatically using web scraping techniques, by utilizing a Python library called google-play-scraper. This library allows researchers to retrieve review data based on applications that are officially registered on the Google Play Store, and supports retrieval of important information such as review content, star rating, and publication date. The data was collected over a period of 2024, with a total of 139.759 reviews collected. This data represents various expressions of user opinions ranging from positive, negative, to neutral comments, which reflect their perceptions and experiences in using the Fizzo Novel application.

3.2. Explore

After the scraping process is carried out, the collected review data is then filtered based on a predetermined time period, namely January to December 2024. This filtering is done to maintain the temporal relevance of the data to the current conditions and user behavior towards the Fizzo Novel application. The distribution of the number of reviews from January to December 2024 is visualized in Figure 2.

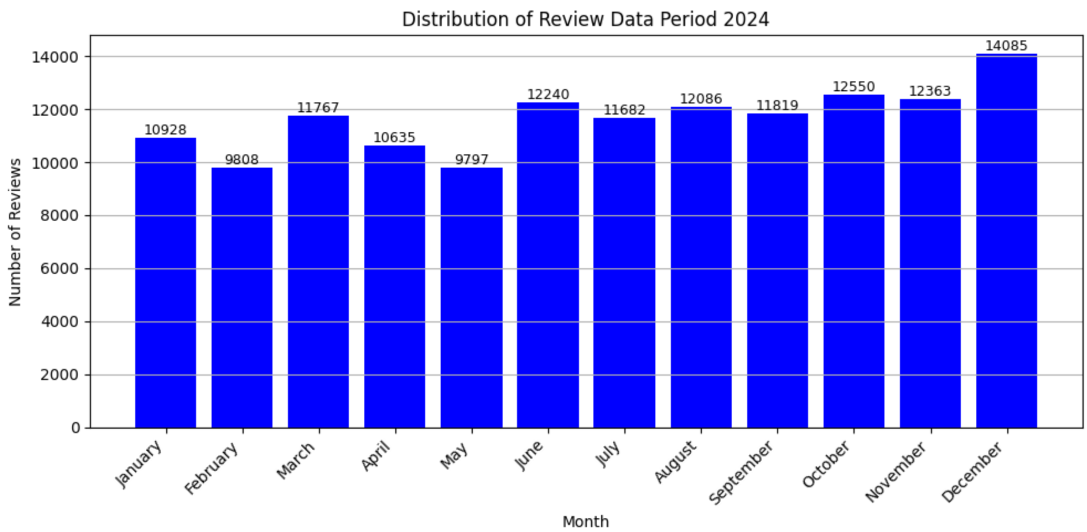

Figure 2. Distribution of Reviews for 2024

Based on the visualization in Figure 2, it can be seen that the number of user reviews of the Fizzo Novel application during the 2024 period fluctuates every month. The most reviews were recorded in December 2024 with a total of 14.085 reviews, while the least reviews occurred in May 2024, which amounted to 9.797 reviews.

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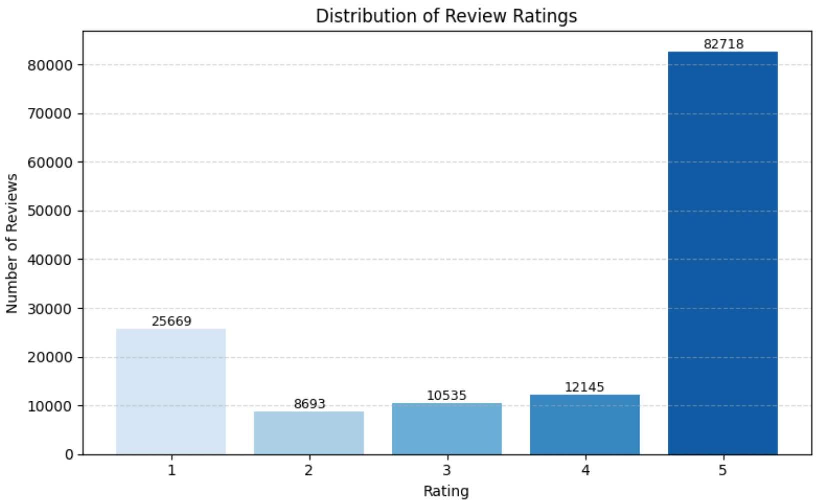

Figure 3. Distribution of Review Ratings

Based on the visualization in Figure 3, it can be seen that the distribution of reviews based on rating shows the dominance of rating 5 as the most given by users, with a total of 82.718 reviews. This rating generally reflects a positive sentiment towards the app. Meanwhile, ratings 1 and 2, which generally represent negative sentiments, have 25.669 and 8.693 reviews respectively, bringing the total number of negative reviews to 34.362. Rating 3, which is considered to represent neutral sentiment, has a total of 10.535 reviews, and rating 4, which also reflects positive sentiment, has 12.145 reviews.

3.3. Modify

After the data has been collected and analyzed in the exploration stage, the next process is to prepare the data for use in modeling. This process begins with a text preprocessing stage that aims to clean the data from various irrelevant elements and ensure the data format is consistent for processing by machine learning algorithms.

3.3.1. Data Prepocessing

The scraping data obtained from Google Play Store is still in a raw and unstructured form, so it cannot be directly used for modeling. Therefore, a series of preprocessing processes are carried out to clean and standardize the data so that it is ready to be used in the modeling stage. The preprocessing stages carried out in this study are as follows:

a). Cleansing

At this stage, data cleaning is performed by removing all non-letter characters, such as punctuation marks, numbers, and other special symbols. This step is important to ensure that only relevant textual information is processed further [26].

b). Case Folding

Case folding is the process of converting all letters in the text to lowercase [27]. The goal is to equalize the representation of words that have the same form but differ in the use of capital letters, such as "Application" and "application", so that they are recognized as the same token by the model.

c). Normalization

Normalization is an important process in handling informal text, especially from user reviews that use a lot of abbreviations or nonstandard words [28]. Words like "gk", "udh", or "bgt" are normalized

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
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to "no", "already", and "really". This process is done using the kaggle library slag dictionary. Normalization helps to unify writing variations thus improving feature quality and increasing model accuracy

d). Tokenizing

Tokenization is performed to break down a sentence or review text into single units of words called tokens [29]. This process allows analysis to be done at the word level, which forms the basis of feature formation for classification.

e). Stopword Removal

This stage includes the removal of irrelevant elements such as URLs, HTML tags, as well as common words that have no significant meaning (stopwords). In addition, this process also filters out words that are too short or irrelevant for further analysis [30]. This process uses the nltk library with the corpus data dictionary.

f). Stemming

Stemming is done to convert each word into its basic or root form [31]. In this research, Indonesian stemming is performed using the Sastrawi library. This stage is important to reduce the number of word variations and strengthen the semantic meaning of the reviews. Although stemming techniques are more commonly applied in English, their use in Indonesian remains relevant to minimize data complexity. Table 1 shows the results of data preprocessing.

Table 1. Data Preprocessing Results

Process	Result
Review Text	Fizzo knp semakin kesini smakin pelit? dl pointnya kelipatan ratusan, skrg cm puluhanðŸ˜ªðŸ˜ªðŸ˜ª, jg males bacanya
Cleansing	Fizzo knp semakin kesini smakin pelit dl pointnya kelipatan ratusan skrg cm puluhan jg males bacanya
Casefolding	fizzo knp semakin kesini smakin pelit dl pointnya kelipatan ratusan skrg cm puluhan jg males bacanya
Normalization	fizzo kenapa semakin kesini semakin pelit dulu pointnya kelipatan ratusan sekarang cuma puluhan juga malas bacanya
Tokenize	['fizzo', 'kenapa', 'semakin', 'kesini', 'semakin', 'pelit', 'dulu', 'pointnya', 'kelipatan', 'ratusan', 'sekarang', 'cuma', 'puluhan', 'juga', 'malas', 'bacanya']
Stopword Removal	['fizzo', 'kesini', 'pelit', 'pointnya', 'kelipatan', 'ratusan', 'puluhan', 'malas', 'bacanya']
Stemming	fizzo kesini pelit point kelipat ratus puluh malas baca

g). Labeling

The labeling process is done using a lexicon-based approach by utilizing the Indonesian sentiment dictionary (InSet Lexicon). In this method, each word in a user review is assigned a sentiment weight based on the polarity value in the dictionary. The accumulative score of all words in a review is used to determine the overall sentiment. Positive scores for positive labels, zero scores for neutral labels, and negative scores for negative labels. Table 2 shows some examples of labeling results obtained through the lexicon-based approach. Each review is assigned a numerical sentiment score which is then converted into category labels.

Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871

https://jutif.if.unsoed.ac.id
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Table 2. Labeling Results

Reviews	Score	Label
Kok tiba-tiba aja koinnya makin dikit gak sampe seribu cok, awalnya 100 jadi 30 jirrr, gimana ini wahhh	-1	Negative
Bermanfaat dan jugak dapet cuan	1	Positive
Kenapa fizzo sekarang dapat koinnya cuma sedikit.padahal sudah berlangganan.tolong dong fizzo jangan membuat pembaca kecewa	0	Neutral

Figure 4 shows the distribution of the number of reviews based on the sentiment class generated from the labeling process. Most user reviews are categorized as positive sentiment with 58.717 reviews (42.01%), followed by neutral sentiment with 55.311 reviews (39.58%), and negative sentiment with 25.732 reviews (18.41%). This distribution shows that in general, the majority of users give a positive assessment of the Fizzo Novel app, although neutral reviews are also quite dominating.

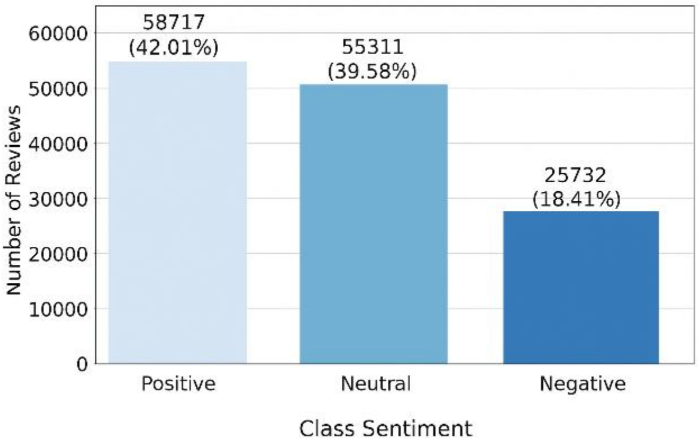

Figure 4. Distribution of Sentiment Results of Labeling

To understand the characteristics of each sentiment, a visualization in the form of a WordCloud is created for each sentiment class. The WordCloud displays the most frequently occurring words in each sentiment category, where the size of the word reflects the frequency of occurrence.

Figure 5. Positive Sentiment WordCloud

Figure 6. Negative Sentiment WordCloud

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P-ISSN: 2723-3863
E-ISSN: 2723-3871

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Figure 7. Neutral Sentiment WordCloud

Based on the WordCloud visualizations in Figures 5, 6, and 7, it can be seen that each sentiment category has different word characteristics. In Figure 5 (Positive Sentiment WordCloud), words such as good, story, and fizzo dominate, illustrating the positive appreciation from users towards the content as well as the reading experience provided by the Fizzo Novel app. Meanwhile, Figure 6 (Negative Sentiment WordCloud) shows the appearance of words such as watch, ads, open, and chapters, which indicate complaints from users about certain features in the application, such as excessive advertising or a chapter division system that is considered annoying. As for Figure 7 (Neutral Sentiment WordCloud), it shows the dominance of words such as advertisement, story, and novel, which indicates that users are delivering informative or flat comments without strong emotional expression

3.3.2. Feature Extraction

At this stage, the review data that has gone through the cleaning and preprocessing process is then converted into a numerical representation using the TF-IDF (Term Frequency-Inverse Document Frequency) method. The purpose of this stage is to convert the set of text into a matrix form that can be processed by machine learning algorithms. From a total of 136.876 review data, data filtering is done by removing entries that contain empty or missing values so that 136.876 clean data remain. Furthermore, these review texts were converted into vectors with TF-IDF Vectorization technique, using max_features=1.000 parameter. This means that from the entire corpus, only the 1.000 most frequently occurring and most relevant unique words (features/tokens) are retained to form the vector representation.

The matrix view of the feature extraction results is shown in Figure 8, which shows the sparse matrix TF-IDF data format. Most of the values in this matrix are zero, indicating that many words do not appear in most documents, as is common in text representations. With this transformation, the review text has been successfully converted into numerical form, ready to be used in the modeling stage using Support Vector Machine (SVM) and Naïve Bayes algorithms.

Kata	D1	D2	D3	D4	D5	...	D136872	D136873	D136874	D136875	D136876
admin	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0
agam	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0
ah	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0
ajar	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0
akses	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...
wawas	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0
wd	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0
wifi	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0
ya	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0
you	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0

Figure 8. TF-IDF Matrix Representation

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3.3.3. Synthetic Minority Oversampling Technique (SMOTE)

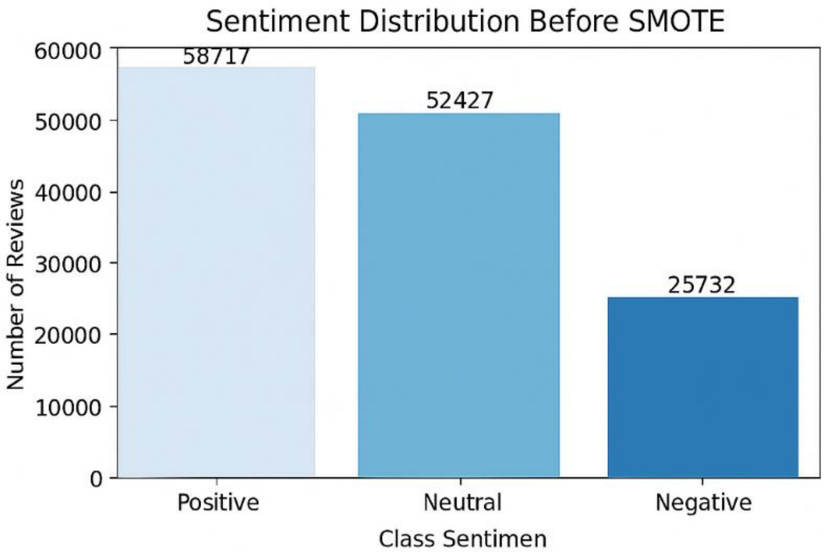

Figure 9. Sentiment Distribution Before SMOTE

The initial analysis results show a significant imbalance in the distribution of sentiment classes. As shown in Figure 9, the number of reviews with positive sentiment is 58.717, neutral is 52.427, and negative is only 25.732. This imbalance has the potential to bias the classification model, especially in recognizing negative sentiment as a minority class. To overcome this problem, training data optimization is carried out using the SMOTE (Synthetic Minority Oversampling Technique) method. SMOTE works by creating synthetic samples in the minority class through an interpolation process between similar data, so as to artificially balance the distribution between classes in a controlled manner.

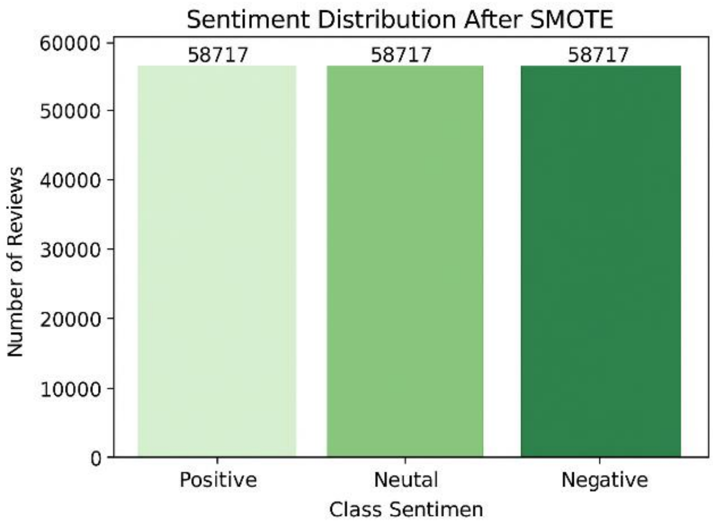

Figure 10. Sentiment Distribution After SMOTE

After the SMOTE process is applied, as shown in Figure 10, the amount of data in each sentiment class becomes balanced, with 58.717 reviews for each positive, neutral and negative class. With this balanced class distribution, the model is expected to recognize and classify the three types of sentiment more fairly and accurately.

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3.4. Model

Before entering the modeling stage, the data that has gone through the preprocessing, labeling, and balancing (SMOTE) process is divided into two parts, namely training data and testing data. The division is done with a ratio of 80:20, where 109.500 data (80%) are used as training data, and 27.376 data (20%) are used as test data. The visualization of this division is shown in Figure 11.

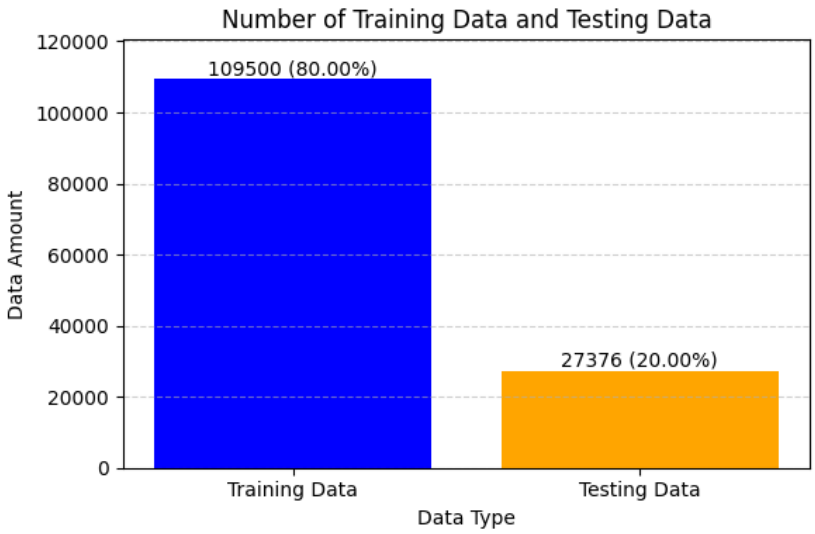

Figure 11. Split Training Data and Testing Data

The decision to allocate a larger proportion of training data aims to provide a wider opportunity for the algorithm to recognize sentiment patterns and characteristics from the available data. The more data used for training, the greater the opportunity for the model to learn the relationship between features more thoroughly, which is expected to improve performance in classifying new data more accurately at the evaluation stage.

3.4.1. Support Vector Machine (SVM)

The evaluation of the Support Vector Machine (SVM) model was conducted before and after the application of the SMOTE technique. Based on Table 3 and Table 4, the SVM performance was very high in both conditions. Before SMOTE, the model recorded 97.10% accuracy, with f1-score above 95% for all classes. The positive class showed the highest performance with a precision of 98.33% and f1-score of 98.35%, while the negative class recorded an f1-score of 95.62%, and neutral 96.41%. After SMOTE, the accuracy decreased slightly to 96.99%, but the distribution of performance between classes remained even. The f1-score of the negative class dropped to 95.34%, and the neutral to 96.28%, while the positive class remained at 98.35%. Overall, the application of SMOTE did not significantly improve accuracy, but contributed to a more balanced distribution of predictions, especially in reducing bias towards the majority class. This makes the SVM reliable despite the changing data distribution conditions.

The performance evaluation of the Support Vector Machine (SVM) model based on the confusion matrix before and after SMOTE in Figure 12 and Figure 13 shows that the model is able to classify most of the data correctly in both scenarios.

Before SMOTE, the model correctly classified 4.813 negative samples, but there were still 310 errors to neutral and 23 to positive. The neutral class recorded 10.216 correct predictions, with 97 errors

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to negative and 173 to positive. Meanwhile, the positive class was predicted very well, with 11.552 correct predictions, and only 181 errors to neutral and 11 to negative.

After SMOTE, the classification results show a slight increase in the negative class, with 4.828 correct predictions, and a decrease in errors to neutral to 295. However, the neutral class decreased slightly with 10.177 correct predictions, and classification errors increased to negative 140 and slightly decreased to positive 169. For the positive class, performance remained stable with 11.548 correct predictions, and similar distribution errors to neutral 182 and negative 14.

Overall, the SVM model performance remained very high both before and after SMOTE. The application of SMOTE slightly improved the distribution of negative classes, but did not significantly change the overall performance. The main challenge is still the misclassification between neutral and positive classes, which shows that ambiguous sentiment expression is still a major bottleneck. Therefore, further improvements can be directed towards optimizing preprocessing and adjusting model parameters to improve separation between classes.

Table 3. SVM Classification Report Results Before SMOTE

Support Vector Machine (SVM) Before SMOTE					
	accuracy	**precision**	**recall**	**f1-score**	**support**
Negative		97.81%	93.53%	95.62%	5.146
Neutral	97.10%	95.41%	97.43%	96.41%	10.486
Positive		98.33%	98.37%	98.35%	11.744

Table 4. SVM Classification Report Results After SMOTE

Support Vector Machine (SVM) After SMOTE					
	accuracy	**precision**	**recall**	**f1-score**	**support**
Negative		96.91%	93.82%	95.34%	5.146
Neutral	96.99%	95.52%	97.05%	96.28%	10.486
Positive		98.36%	98.33%	98.35%	11.744

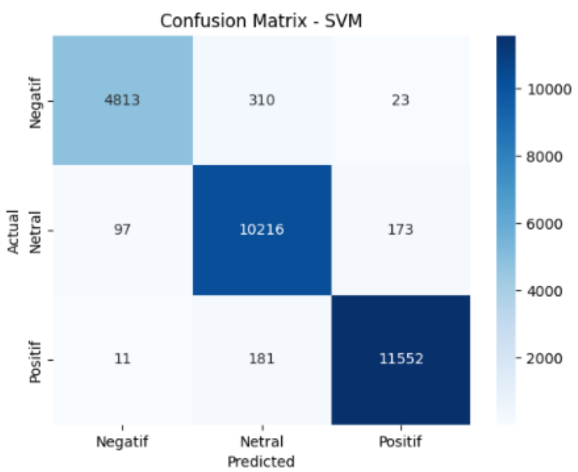

Figure 12. Confusion Matrix of SVM Model Before SMOTE

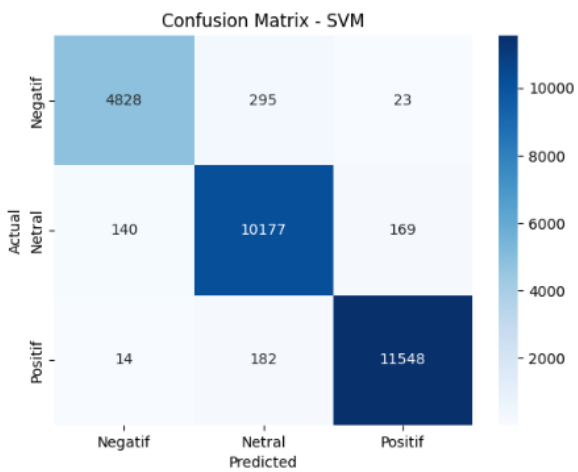

Figure 13. Confusion Matrix of SVM Model After SMOTE

Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871
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https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4875

3.4.2. Naïve Bayes

The evaluation of the Naïve Bayes model in the pre- and post-SMOTE scenarios shows varying results between classes, as shown in Table 5 and Table 6. Before SMOTE, the model recorded an accuracy of 75.82%, with the highest performance in the positive class (f1-score 82.34%), while the negative and neutral classes were at 69.25% and 70.98% respectively. After SMOTE, the accuracy decreased to 73.63%, with increased recall in the negative class (83.54%), but accompanied by a significant decrease in precision (50.31%), causing the f1-score to drop to 62.80%. The performance of the neutral class also decreased, while the positive class experienced an increase in f1-score to 84.18%, supported by a precision that increased to 89.16%. This finding shows that SMOTE helps the model recognize more minority data, but increases the risk of misclassification on majority data. This has an impact on probabilistic models such as Naïve Bayes, which tend to be less flexible to synthetic data that does not represent natural distributions.

Table 5. Naïve Bayes Classification Report Results Before SMOTE

Naïve Bayes Before SMOTE					
	accuracy	**precision**	**recall**	**f1-score**	**support**
Negative		72.27%	66.09%	69.25%	5.146
Neutral	75.82%	74.20%	68.02%	70.98%	10.486
Positive		78.11%	87.04%	82.34%	11.744

Table 6. Naïve Bayes Classification Report Results After SMOTE

Naïve Bayes After SMOTE					
	accuracy	**precision**	**recall**	**f1-score**	**support**
Negative		50.31%	83.54%	62.80%	5.146
Neutral	73.63%	77.99%	61.94%	69.04%	10.486
Positive		89.16%	79.73%	84.18%	11.744

The performance evaluation of the Naïve Bayes model based on the confusion matrix before and after SMOTE in Figure 14 and Figure 15 shows that the model is quite good at classifying positive and negative sentiments, but still experiences challenges in distinguishing neutral sentiments.

Before SMOTE, the model correctly classified 3.401 negative samples, but there were still 1.348 samples misclassified as neutral and 397 as positive. For the neutral class, there were 7.133 correct predictions, with 886 misclassifications to negative and 2.467 to positive. Meanwhile, the positive class performed the best with 10.222 correct predictions, and misclassifications of 1.132 to neutral and 390 to negative.

After SMOTE, there was an improvement in the classification accuracy of the negative class with 4.299 correct predictions, as well as a decrease in errors to neutral to 689 and to positive by 158. However, performance on the neutral class decreased, with only 6.495 correct predictions, while errors to negative increased to 3.010 and to positive 981. For the positive class, the number of correct predictions decreased to 9.364, with errors to neutral of 1.144 and to negative of 1.236.

Overall, the application of SMOTE helps to improve the classification of the negative class, but causes a decrease in performance especially in the neutral class. This shows that although the data distribution becomes more balanced, the model still struggles to distinguish neutral sentiments that tend

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P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4875

to be ambiguous. Further improvements can be focused on better preprocessing techniques and model parameter tuning to improve classification accuracy, especially in distinguishing the neutral class from other classes.

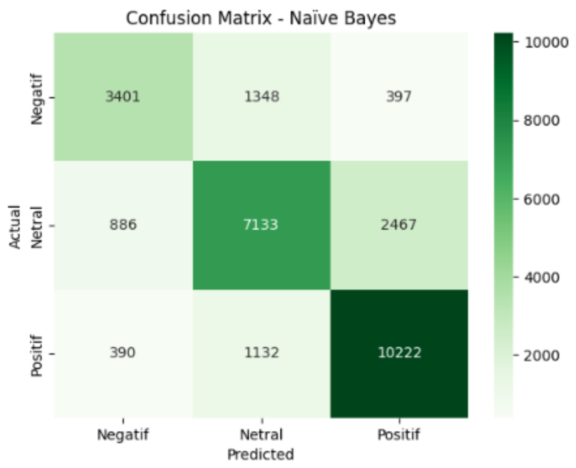

Figure 14. Confusion Matrix of Naïve Bayes Model Before SMOTE

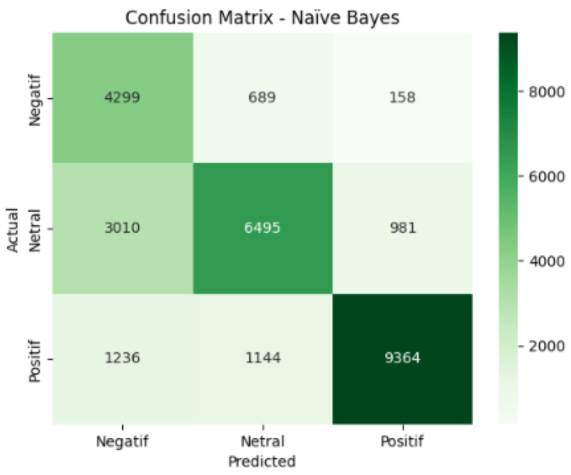

Figure 15. Confusion Matrix of Naïve Bayes Model After SMOTE

3.5. Assess

The Assess stage is the final part of the SEMMA method used to assess how well the sentiment analysis model was built. In this study, two algorithms were used: Support Vector Machine (SVM) and Naïve Bayes, each of which was tested before and after applying the SMOTE technique to balance the amount of data from each type of sentiment.

The test results show that the SVM model performs better than Naïve Bayes. After applying SMOTE, the accuracy of SVM reached 96.99%, while Naïve Bayes only achieved 73.63%. In addition, SVM also showed more stable results in recognizing three types of sentiment, namely positive, neutral, and negative. On the other hand, the performance of Naïve Bayes tended to fluctuate, especially in detecting neutral sentiment. Although this algorithm was able to recognize more minority data after SMOTE, its prediction results became less accurate due to a decrease in precision.

To clarify the comparison of algorithm performance, Figure 16 below presents a bar chart visualization comparing the accuracy levels of the SVM and Naïve Bayes models after SMOTE.

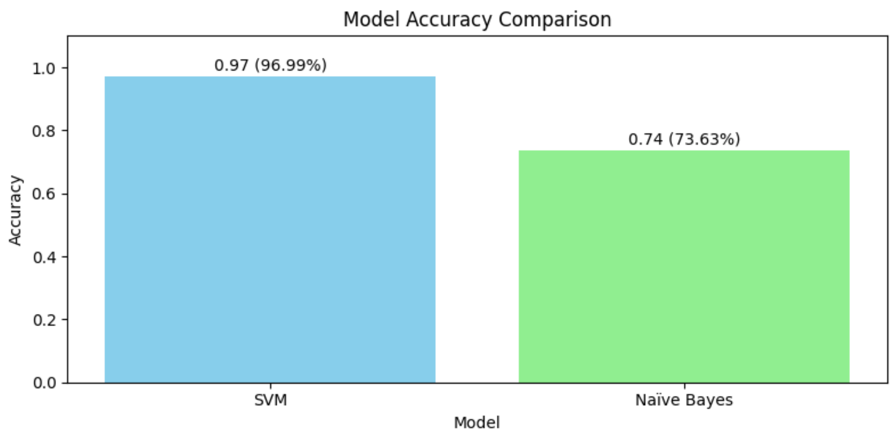

Figure 16. Comparison of the Accuracy of SVM and Naïve Bayes Models After SMOTE

P-ISSN: 2723-3863
https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4875

From the image, it can be seen that SVM is overall superior to Naïve Bayes in sentiment classification. This shows that SVM is more effective in handling unbalanced data and more reliable in recognizing various expressions of user opinion.

In addition to serving as an analytical tool, the findings of this study also have practical applications. First, sentiment analysis can assist developers of the Fizzo Novel app in identifying features most frequently criticized by users, such as intrusive ads or the chapter-sharing system. This information can serve as a basis for improving the quality and user experience of the app in line with user expectations. Second, the proven accurate SVM model can be used to monitor user opinions automatically and in real-time, enabling developers to detect complaints more quickly and evaluate changes made through app updates.

Overall, this study demonstrates that the application of machine learning-based sentiment analysis is not only useful for academic purposes but also directly beneficial in aiding more precise decision-making in digital app development.

4. DISCUSSIONS

4.1. Previous Research

Previous studies on sentiment analysis of digital applications have shown that classification algorithms such as Support Vector Machine (SVM) and Naïve Bayes are commonly used approaches due to their ability to handle subjective text data. The results obtained tend to be competitive, but SVM consistently shows slightly superior performance in some implementation contexts. In a study conducted on Tinder user reviews, for example, the application of the Synthetic Minority Oversampling Technique (SMOTE) proved effective in balancing the class distribution of the data, which in turn had a positive impact on model accuracy. Test results showed that SVM was able to achieve 85% accuracy, slightly higher than Naïve Bayes which recorded 84% accuracy. In addition, SVM also shows better consistency in recognizing both sentiment poles, namely positive and negative, without being overly biased towards either category [13].

Similar findings were also obtained in the analysis of the Pluang investment application, where the accuracy of the SVM model was recorded at 99.50%, slightly ahead of Naïve Bayes which obtained 99.25%. Although the difference is not large, this still confirms the structural advantage of SVM in mapping data into a high-dimensional space through the use of kernels, making it more effective in modeling complex relationships between features. This ability is especially important when the model is faced with data with diverse and non-explicit sentiment patterns [11].

Furthermore, research on social media application X highlighted the significant impact of applying the SMOTE technique on classification performance. Before optimization, SVM accuracy was only 75.5%, but increased to 81% after SMOTE was applied. In contrast, Naïve Bayes showed a relatively stagnant performance, staying at 75.5% accuracy even after the class distribution was balanced. This fact indicates that SVM not only excels in terms of complex feature-based classification, but is also more adaptive to data distribution improvements, making it a more flexible choice in sentiment analysis scenarios involving unbalanced data [32].

The Support Vector Machine (SVM) algorithm demonstrates better performance than Naïve Bayes in analyzing sentiment in high-dimensional text data. SVM achieves an accuracy rate of over 96% with a balanced F1-score across all sentiment classes (positive, neutral, and negative). This indicates that SVM is more reliable in handling large and imbalanced datasets.

SVM has proven to be superior to Naïve Bayes in sentiment analysis of large and imbalanced text data. This study recommends SVM as the primary algorithm for sentiment analysis in digital applications such as Fizzo Novel, particularly to enhance understanding of user opinions and support data-driven decision-making.

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4.2. Interpretation of Results

From the experimental results conducted on the Support Vector Machine (SVM) and Naïve Bayes models in sentiment classification of user reviews of the Fizzo Novel application, findings were obtained that showed quite contrasting model performance before and after the application of the SMOTE technique. The SVM model consistently recorded very high performance in both scenarios, with accuracy reaching 97.10% before SMOTE and slightly decreasing to 96.99% after SMOTE. Despite the slight decrease, the distribution of predictions between classes became more balanced, especially in the negative class which previously had minority representation.

The SVM model also showed balanced precision, recall, and F1-score values across all classes, especially for positive sentiment which always recorded the highest performance. This shows that SVM is able to generalize well and is not overly biased towards one particular class. In contrast, Naïve Bayes recorded a lower accuracy of 75.82% before SMOTE and decreased to 73.63% after SMOTE. This decrease in accuracy is due to the increase in misclassification, especially in the neutral and negative classes after the class distribution is artificially balanced. Although recall for the negative class increased, the decrease in precision caused the overall f1-score to decrease, indicating a significant trade off after SMOTE was applied to the Naïve Bayes model.

These results indicate that while both models can handle the sentiment classification task, SVM is superior in the context of the Fizzo Novel dataset which has a diversity of opinion expressions and a previously unbalanced sentiment distribution. The advantage of SVM lies in its ability to handle highdimensional features and the synthetic data characteristics of SMOTE results more stably. Meanwhile, the performance of Naïve Bayes, which tends to be more affected by data distribution, shows its limitations in absorbing pattern variations from minority classes and ambiguities in neutral sentiments.

Overall, the selection of the best model needs to be tailored to the purpose of the analysis. If high accuracy and stable performance across classes are prioritized, then SVM can be considered as a more reliable choice. This finding is in line with several previous studies that show the superiority of SVM in sentiment analysis, especially in the context of digital applications with large data volumes and uneven sentiment distribution. Nevertheless, model flexibility and computational efficiency remain a consideration in the final implementation according to the specific needs of the analyzed application.

5. CONCLUSION

This research successfully implements the SEMMA framework in sentiment analysis of Fizzo Novel app reviews obtained through web scraping techniques from the Google Play Store platform. From a total of 139,759 user reviews, a series of processes were carried out, starting from preprocessing, lexicon-based labeling, feature extraction using the TF-IDF method, to data balancing through the SMOTE technique. The experimental results showed that the Support Vector Machine (SVM) algorithm produced the most optimal classification performance, both before and after SMOTE application, with accuracy above 96% and high F1-score values across all sentiment classes, particularly for positive sentiment. In contrast, the Naïve Bayes algorithm showed lower performance, with an accuracy of 75.82% before SMOTE and a decrease to 73.63% after SMOTE, with the most significant decrease occurring in the neutral sentiment class. Although the application of SMOTE did not directly improve overall accuracy, this technique proved effective in balancing class distribution and improving recall in minority classes.

Overall, SVM proved to be more reliable in handling imbalanced and high-dimensional text data compared to Naïve Bayes, which tends to be more sensitive to noise due to the oversampling process. However, this study has several limitations. First, the algorithms tested were limited to SVM and Naïve Bayes, so the scope of model performance evaluation remains limited. Second, although the data used

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was large, all reviews were from a single application (Fizzo Novel) on a single platform (Google Play Store), making the results of this study not necessarily generalizable to other application contexts.

Based on this, further research is recommended to explore more complex algorithms, such as Long Short-Term Memory (LSTM), Bidirectional Encoder Representations from Transformers (BERT), or other deep learning-based models that can capture semantic context more deeply. Additionally, using a more diverse dataset, whether from similar apps in different categories or from other platforms, can be used to test the consistency of model performance and enhance the generalizability of research results. Furthermore, combining with alternative data balancing techniques besides SMOTE, such as ADASYN or cluster-based undersampling, can also be considered to reduce potential noise and improve classification accuracy, particularly in distinguishing neutral sentiment that tends to be ambiguous. By considering the existing limitations and directing further research toward these aspects, machine learning-based sentiment analysis is expected to become an increasingly effective tool for understanding user needs and supporting data-driven decision-making in the development of digital applications.

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