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Sentiment Analysis of NTB Syariah Bank Application Services using The Naïve Bayes and Support Vector Machine Methods

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ABSTRACT

This research analyzed user sentiment toward the NTB Syariah application using Support Vector Machine (SVM) and Naïve Bayes classification methods. A dataset comprising 814 reviews was obtained via web scraping, with 245 allocated for testing. Preprocessing encompassed cleaning, case folding, tokenization, filtering, and stemming, while sentiment labeling employed a lexicon-based approach integrated with TF-IDF weighting, categorizing reviews as positive, neutral, or negative. Model performance was assessed through accuracy, precision, recall, and F1-score metrics. Results demonstrated SVM's superior performance (accuracy: 92.65%; precision: 0.9327; recall: 0.9265; F1-score: 0.9149) compared to Naïve Bayes (accuracy: 84.49%; precision: 0.8415; recall: 0.8449; F1-score: 0.8005). SVM exhibited greater robustness in managing high-dimensional, complex, and moderately imbalanced datasets, delivering consistent cross-class sentiment classification. Conversely, Naïve Bayes remained computationally efficient and suitable for rapid implementation scenarios. These findings underscore machine learning's efficacy in sentiment analysis for digital banking platforms.

INTRODUCTION

The advancement of information and communication technology is currently accelerating in human life [1]. We are currently in the era of Industry 4.0, which means that technology is being utilized in all aspects of life. This has certainly driven significant transformation in the financial services sector, particularly through the digitization of banking services. With the increasing use of smartphones, the need for fast, accessible, and efficient banking services has become increasingly crucial [2]. Banks in Indonesia are beginning to compete in developing mobile applications to reach a wider range of customers [3]. One of them is Bank NTB Syariah, which has launched a mobile application to facilitate various digital financial transactions for its customers.

However, amid the increase in application adoption, various user complaints persist, including limited payment methods and lengthy transaction processes. This has the potential to reduce user satisfaction and trust in these digital banking services. These complaints are typically conveyed through user reviews on digital platforms, such as the Google Play Store or social media [4]. However, they are not yet well organized or classified. The absence of labeling or grouping of comments makes it difficult for management to quickly and thoroughly understand user sentiment [5].

Several studies have applied text classification methods to analyze sentiment in mobile banking app reviews. Research on the Victoria Mobile Banking app used the NB method and reported very good results: 93.1% accuracy, 90.4% precision, 100% recall, and a 95% F1-score [3]. Conversely, another study evaluating the BSI Mobile app after a ransomware incident used the SVM algorithm, attaining an accuracy of 77%, 72% precision, 83% recall, and 77% F1-score [6]. Researchers in another study compared NB, SVM, and KNN on the Wonder by BNI app and found that SVM provided the highest accuracy. However, the exact accuracy was not specifically mentioned [6]. Additionally, another study reported that the NB method achieved 83.06% accuracy [7].

In comparison, the KNN method is slightly superior with an accuracy of 84.06% in Jenius application reviews. Researcher [8] evaluated the effectiveness of the NB, SVM, and Random Forest algorithms on reviews of the Halo BCA application, using a dataset of 6,464 entries taken from the Google Play Store. The results from the test indicated that the Random Forest algorithm showed the best performance, achieving a precision, recall, and F1-score of 0.91. Coming in second place, SVM reported an accuracy of 87.55% and maintained a precision, recall, and F1-score of 0.88 across the board. In the meantime, NB achieved an accuracy of 81.73% and a precision of 0.83, along with recall and F1-score of 0.82. Although similar results in previous studies show the effectiveness of each method in certain contexts, most are still limited to general types of applications, such as social media and e-wallets [9].

Therefore, a study is needed that specifically tests the performance of sentiment classification algorithms in the Islamic banking domain, especially for reviews of the Bank NTB Syariah application, which remain largely unexplored. This research aims to fulfill this requirement by applying and evaluating the NB and SVM algorithms on user feedback for the Bank NTB Syariah app, utilizing a lexicon-driven method for preliminary labeling and evaluation, with a focus on metrics such as accuracy, precision, recall, and F1-score. Thus, this approach is expected to make a practical contribution to enhancing the quality of Islamic banking digital services by providing a systematic understanding of user opinions. Although previous studies have proven the effectiveness of the NB and SVM methods in sentiment analysis, most of these studies are still limited to general application contexts, such as social media, e-commerce platforms, and traditional mobile banking services [10].

To date, no research has been found that analyzes explicitly user reviews of the Bank NTB Syariah application using a sentiment analysis approach. In fact, banking services based on Sharia principles have distinct characteristics and user perceptions compared to conventional services, so an appropriate classification approach is necessary. Therefore, this study aims to overcome these deficiencies by applying and comparing the NB and SVM algorithms in classifying user sentiment reviews of the NTB Syariah Bank application into three categories: positive, negative, and neutral [8]. As a solution, a system is needed that can automatically categorize user comments into positive, negative, and neutral sentiments [11].

To meet these requirements, this study proposes the use of text classification methods based on the NB and SVM algorithms. The NB method is known to be efficient for large datasets with simple patterns [12]. In contrast, SVM excels at handling high-dimensional and complex data [13]. The comment labeling process was carried out with a lexicon-driven approach, leveraging a sentiment dictionary to assess the polarity of specific words or phrases. This study applies and compares the performance of NB and SVM algorithms in classifying user review sentiments for the Bank NTB Syariah application. The classification process is used to determine the effectiveness of each algorithm in categorizing sentiments as positive, negative, or neutral [14].

The results of this study are expected to contribute to the development of an automated sentiment analysis system for processing text-based reviews from users of digital banking applications, particularly the Bank NTB Syariah application. This research highlights the importance of banking application services that are responsive to user opinions and experiences so that feature development and service quality can be carried out in a targeted and data-driven manner. Technically, this research serves as a reference in the application of machine learning and lexicon-based approaches, which support systematic and efficient evaluation of application services. In addition, this study evaluates the performance of the NB and SVM algorithms in classifying user reviews into positive, negative, and neutral categories, where NB is suitable for large data sets and simple patterns [15], based on word probabilities in documents, while SVM utilizes optimal class separation in high-dimensional and complex data [16]. The comparison of the two algorithms aims to obtain an overview of the effectiveness and efficiency of the methods in analyzing user opinions of applications, while exploring the potential application of sentiment classification systems as independent, adaptive, and efficient analytical solutions to support the development and improvement of the quality of digital banking application services on an ongoing basis.

METHODS

This study begins with retrieving user review data from the Google Play Store using a web scraping method. The collected raw dataset then enters the preprocessing stage, which consists of several steps: cleaning to remove noise such as emojis, symbols, and irrelevant characters; case folding to standardize all text into lowercase; tokenizing to split sentences into individual tokens; filtering to remove stop words or words that do not contribute to meaning; and stemming to convert words into their base forms [17].

After preprocessing, the cleaned text data proceeds to labeling, where each review is categorized into the appropriate sentiment class. The labelled data is then transformed using TF- IDF feature extraction to convert text into numerical vectors. Because the dataset contains class imbalance, an oversampling technique is applied before forming the training dataset. The balanced training dataset is then used for sentiment classification using two algorithms, NB and SVM. Finally, the performance of both models is evaluated using accuracy, precision, recall, and F1-score, and the results are displayed as the final output of the research [17].

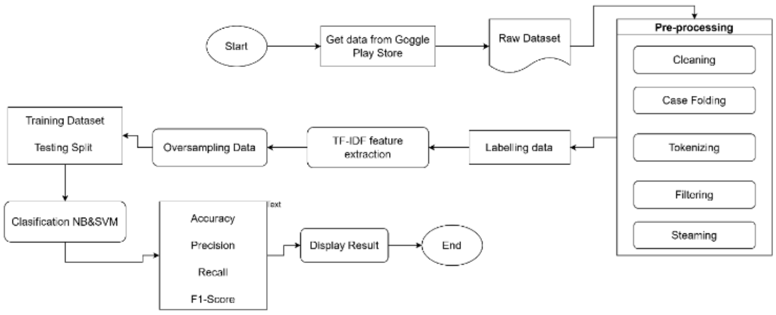


Figure 1. Research Flow

Data Collection

Data collection involved utilizing Python programming to carry out web scraping on the Google Play Store, gathering user reviews for the NTB Syariah Bank app. The data obtained is still in raw dataset form and has not been processed, so further steps are required before it can be used for sentiment analysis [20].

Preprocessing Data

Data preprocessing is intended to simplify and clean up data so that it is more relevant and understandable by machines. This stage is crucial because data quality has a significant impact on the final classification results [21]. Several stages carried out in data pre-processing are as follows [22]:

a) Cleaning: Cleaning data from special characters, punctuation marks, URLs, numbers, or other irrelevant elements so that the data is ready for processing [23].
b) Case Folding: Change all the text to lowercase to maintain uniformity and eliminate variations caused by capital letters [23].
c) Tokenizing: Breaking down review text into word units or tokens for easier analysis [23], [24].
d) Filtering: Removing words that have no significant meaning or are irrelevant in the context of the analysis so that the model can focus on the main keywords [23].
e) Stemming: Remove affixes such as prefixes, suffixes, or infixes from words to simplify them to their root form and reduce word variation [23].
f) Labelling Data: Assigning sentiment labels to each processed review based on predefined categories (such as positive, negative, or neutral). This step is important because labelled data serves as the foundation for supervised learning in the next stages [20].
g) TF-IDF Feature Extraction: Transforming the cleaned text into numerical vectors using the TF-IDF (Term Frequency–Inverse Document Frequency) method. This process highlights important words in each review by considering their frequency and relevance, making the text suitable for machine learning algorithms [15].
h) Oversampling Data: Handling class imbalance by increasing the number of samples in minority classes. Oversampling ensures that the classification model does not become biased toward the majority class and can learn more effectively [21].
i) Training & Testing Dataset: The dataset is divided into training and testing with a 70:30 ratio. The training dataset is used to train the model, while the testing dataset is used to evaluate the model's performance [22].
j) Classification (Naive Bayes & SVM): Applying machine learning algorithms—Naive Bayes and Support Vector Machine—to classify sentiments based on the processed and vectorized data. Each model learns patterns from the training data to make predictions [23].
k) Display Result: Presenting the evaluation outcomes of each classification model, including metrics such as accuracy, precision, recall, and F1-score, in graphical form. This step provides a clear comparison of model performance as the final output of the study [23].

Next, after the preprocessing stage is completed, the dataset proceeds through the labeling process and oversampling before being used as the training dataset for building the classification model, without being separated into a specific testing subset.

Labelling Data

The processed text will be labeled based on a predetermined set of words in the lexicon. Each word in the text will be matched with words in the lexicon-based, and then the system will assign a sentiment label to the text. Sentiment can be positive (+1), negative (−1), neutral (0), or other labels predetermined according to the specific needs of the analysis [24]. The sentiment score of each matching word will be calculated, then to added up with this equationn to obtain the total sentiment score of the text [25].

$$Sentiment\_Score\ (S^i) = \sum_{i=1}^{n} S_i$$

The data labeling process is an important step in data processing, where each review text is automatically assigned a sentiment label such as “positive”, “negative”, or “neutral” using a lexicon-based approach [22]. In this method, words in the review are matched against a dictionary containing pre-assigned sentiment scores, for example +1 for positive, -1 for negative, and 0 for neutral. The overall sentiment of the text is determined by aggregating these scores [23]. This automated labeling approach removes the need for manual assessment, allowing machine learning models to efficiently learn sentiment patterns and enhancing the overall efficiency of data analysis [21].

Word Weighting

Word weighting aims to assign a value or weight to each word in a document, allowing more relevant or essential words to be identified and analyzed more effectively in a specific context. The stages of word weighting [27] are as follows in these equations [28]. Term Frequency (TF) describes the number of times a word occurs within a text, and can be a factor [28].

$$TF(t,d) = \frac{f(t,d)}{N}$$

Document Frequency (DF) measures the frequency of a word's occurrence across all documents. This document frequency value is later used to calculate inverse document frequency [28].

$$DF(t) = |\{d \in D: t \in d\}|$$

Inverse Document Frequency (IDF) functions to measure the overall importance of a word. This method gives greater weight to words that appear infrequently, as these words tend to be more informative [28].

$$idf_t = log10\left(\frac{N}{df_{(t)}}\right)$$

Naïve Bayes Classification

NB is a probability-based classification algorithm based on Bayes' theorem, proposed by Thomas Bayes [17]. This method is widely used in sentiment analysis, text classification, and various machine learning applications due to its simplicity and effectiveness [17]. The term NB is used because this algorithm assumes that each attribute is independent of the others, with a statistical approach. NB estimates the likelihood that a given observation belongs to a specific class [17].

$$P(C \mid X) = \frac{P(X|C).P(C)}{P(X)}$$

All features are independent of each other, probability likelihood P(X|C)P(X|C)[17] where variable xi is an individual feature, and variable n is the number of features [17].

$$P(X|C) = \prod_{i=1}^{n} P(xi|C) \tag{6}$$

SVM Classification

SVM is a form of supervised learning used for tasks involving classification and regression. It works by creating a hyperplane within a high-dimensional space [29]. SVM operates by optimizing the separation boundary between categories, which makes it suitable for distinguishing intricate and nonlinear datasets [4]. This method is widely applied in text classification, image object detection, and bioinformatics, and remains one of the most widely used algorithms in machine learning [30]. The main advantage of SVM lies in its ability to overcome overfitting problems by utilizing the maximum margin principle [4].

Additionally, SVM can be combined with kernel functions to handle data that cannot be linearly separated. With these characteristics, SVM is often chosen in research that requires high accuracy in large-dimensional data [30], [29].

$$K(x_i, x) = x_i x$$

Polynomial Kernel is one type of kernel used in algorithms (SVM) and other machine learning methods for classification and regression [31].

$$K(x_i, x) = (x_i x)d$$

The Gaussian kernel or Radial Basis Function (RBF) is a technique used in machine learning algorithms, especially in SVM [31].

$$K(x_i, x) = exp\left(\frac{-\|x_i - x\|2}{2\sigma^2}\right)$$

The Sigmoid kernel is a type of kernel widely used in SVM algorithms [31].

$$K(x_i, x) = \tanh(\sigma(x_i\, x) + c)$$

In the SVM data classification procedure, Equation (10) is employed, where x represents the accessible data or a training data sample. Meanwhile, variable w denotes the weight vector, and variable b stands for a scalar value [31].

$$f(x) = w.x + b$$

The above formula describes the function f(x) used in the classification process with SVM. This function accepts data to be classified, denoted by x, and returns the corresponding class label [30]. The variable xi refers to the training data, while yi is the class label associated with that training data. The weight of each training data is represented by ai . The kernel function, denoted by $K(xi,x)$ is applied to each training data point. The parameter b is the bias used in the classification process. Using this function, SVM can predict the appropriate class label for the data to be classified based on the information obtained from the training data and the calculated weights [31].

Evaluation Model

When assessing the effectiveness of classification models, some of the frequently utilized metrics include accuracy, precision, and recall The calculation of these metrics depends on the confusion matrix, which is a tool that maps the model's predictions against the real outcomes across four categories: True Positive (TP) involves cases where positive instances are correctly predicted as positive, whereas True Negative (TN) involves situations where negative instances are accurately identified as negative. False Positive (FP) refers to scenarios where negative cases are incorrectly labeled as positive, and False Negative (FN) deals with situations where positive instances are misclassified as negative. The confusion matrix serves as the foundation for determining other performance metrics, such as sensitivity and the F1-score [32].

1) Accuracy refers to the degree to which the predicted value of a model aligns with the actual value. The model results can be considered more accurate if they yield an accuracy value close to 100% [33].

$$Accuracy\ \frac{(TP + TN)}{(TP + TN + FP + FN)}\ x\ 100\%$$

2) Recall, also known as sensitivity, is a technique utilized to evaluate the effectiveness of a model in accurately categorizing positively labeled data overall [33].

$$Recall = \frac{TP}{(TP + FN)} x100\%$$

3) Precision is utilized to evaluate the accuracy of a model designed to classify data into positive categories [33].

$$Precision = \frac{TP}{TP + FP} x\ 100\%$$

4) The F1 score is the ratio of the average recall and precision [33].

$$F1\ score = 2x\ \frac{RecallxPrecesion}{Recall + Precesion} x\ 100\%$$

RESULTS AND DISCUSSION

This research gathered data by employing web scraping techniques, with a particular focus on user reviews for the Bank NTB Syariah application available on the Google Play Store. The collected dataset comprises user reviews from December 2023 to March 2025, totaling 814 review data points. Table 1 described the scraping results are stored in CSV file.

Table 1. Scraping CSV Data

Score	Date	Content
5	29/03/2025	*Sangat Bermanfaat 👍👍 Dan dapat digunakan kapanpun sengat membantu selalu jadi yang terdepan 🙏😃*
3	23/12/2024	*Aduh sudah berapa bulan belum saja bisa kapan bisa nya ini aplikasi transfers susah*
1	17/06/2025	*Transfer antar bank tidak bisa transfer sesama bank tidak bisa juga notifikasi tidak diberitahukan juga baik dari sms dan notifikasi pada tab ponsel, lelet sering keluar sendiri. Jujur kecewa karna bukanya memudahkan malah jadi menyulitkan.*
2	09/07/2025	*App nya ga bisa dipakai transaksi,isi pulsa,transfer dan dompet digital,cuman bisa cek saldo.. parah*
4	01/07/2025	*Layanan m banking NTB Syariah sudah bagus tapi masih perlu meningkatkan,apalagi kemarin sempat bermasalah,tidak bisa melakukan transaksi diluar bank ntb syariah semoga kedepan nya semakin baik karna bank ini merupakan andalan ASN NTB*

Once the data collection is finished, the gathered information cannot be analyzed right away due to the presence of considerable noise. As a critical component of data mining, data pre-processing is designed to transform raw data into a more organized format that is prepared for analysis, while eliminating irrelevant elements in subsequent steps. This process includes data cleaning, case folding, tokenization, stopword removal, and stemming.

Table 2. Pre-processing Results

Raw Data	
Sangat Bermanfaat 👍👍 Dan dapat digunakan kapanpun sengat membantu selalu jadi yang terdepan 🙏😃	
Text Pre-processing	
Cleansing	*sangat bermanfaat dan dapat digunakan kapanpun sengat membantu selalu jadi yang terdepan*
Case Folding	*sangat bermanfaat dan dapat digunakan kapanpun sengat membantu selalu jadi yang terdepan*
Tokenization	*'sangat', 'bermanfaat', 'dan', 'dapat', 'digunakan', 'kapanpun', 'sengat', 'membantu', 'selalu', 'jadi', 'yang', 'terdepan'*
Normalization	*'sangat', 'bermanfaat', 'dan', 'dapat', 'digunakan', 'kapanpun', 'sangat', 'membantu', 'selalu', 'jadi', 'yang', 'terdepan'*
Filtering	*'sangat', 'bermanfaat', 'sangat', 'membantu', 'terdepan'*
Steaming	*'sangat', 'manfaat', 'sangat', 'bantu', 'depan'*

Table 3. Labeling Results

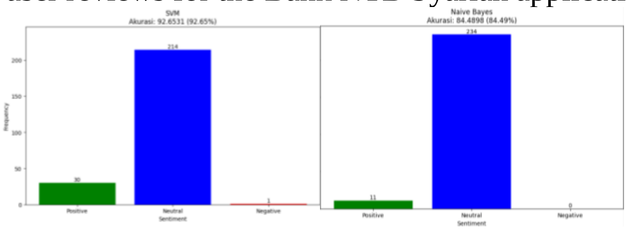
Text Clean	Score	Sentiment
knp tidak bisa daftar m bangking	+1	Positive
aduh sudah berapa bulan belum aja bisa kapan bisanya ini aplikasi transfer susah	−1	Negatif
mohon penjelasan kenapa tidak bisa beli pulsa hp sama transfer ke bank lain	0	Netral

Once the data labeling process is finished, the information is organized into categories to identify how frequently the most common words occur. These frequencies are then presented visually through a word cloud. Every review is associated with a distinct set of words, which are categorized as positive, negative, or neutral. Words like "very," "benefit," "help," "okay," and "investment" frequently appear in positive reviews, as depicted in Figure 2 (a). In Figure 2 (b), it is shown that words such as "can," "bank," "application," "no," and "not" are frequently found in negative reviews. Figure 2(c) demonstrates that terms like "can," "no," "I," "application," and "bank" are most commonly seen in neutral reviews.

(a)Positive Word Cloud (b) Negative Word Cloud (c) Neutral Word Cloud

Figure 2. The Frequency of The Most Frequently Occurring Words

The feature extraction process was carried out using the TF-IDF method in Python, which converted user reviews into word-weight-based vector representations. Next, review data from Google Play Store for the Bank NTB Syariah app, which has a total of 814 reviews. The data was tested using two classification algorithms: SVM and NB. After the data was processed, a classification model was created to predict user sentiment. The classification results were then used to assess user percDeptions of the application based on available reviews. Figure 3 shown a sentiment analysis of user reviews for the Bank NTB Syariah application using NB and SVM



(a) SVM Classification (b) NB Classification

Figure 3. Classification Model

The results of the NB classification method are shown in Figure 3(b). Of the total 814 labeled reviews, 245 data were used as test samples, and the Naive Bayes model successfully classified 11 reviews as positive, 234 as neutral, and 0 as negative, with an accuracy of 84.49%. The classification performance of the SVM model is shown in Figure 3(a). Using the same 245 test samples, the SVM model classified 30 reviews as positive, 214 as neutral, and 1 as negative, with an accuracy of 92.65%. Further evaluation of the model was performed using a matrix to obtain accuracy, precision, recall, and f1-score values.

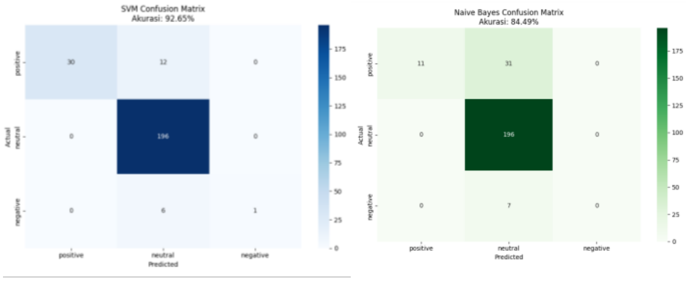


Figure 4. Confusion Matrix

Table 4. Confusion matrix result

	Accuracy	**Precision**	**Recall**	**F1-Score**
SVM	92.65%	0.9327	0.9265	0.9149
NB	84.49%	0.8415%	0.8449%	0.8005%

The results in Table 4 indicate that both SVM and NB are capable of performing sentiment classification effectively. The SVM model achieved an accuracy of 92.65%, a precision of 0.9327, a recall of 0.9265, and an F1-score of 0.9149. Meanwhile, the NB model obtained an accuracy of 84.49%, a precision of 0.8415, a recall of 0.8449, and an F1-score of 0.8005. Based on this comparison, SVM demonstrates superior performance across all evaluation metrics. This suggests that SVM is more consistent and reliable in identifying sentiment classes, while NB remains competitive but tends to be less accurate compared to SVM in handling the classification tasks.

CONCLUSION AND RECOMMENDATIONS

Based on the results of sentiment analysis on user reviews of the Bank NTB Syariah application on the Google Play Store, a total of 814 review data were obtained and divided into training and test sets, resulting in 245 reviews being used as test data. This study applied two classification algorithms, namely SVM and NB, to classify user sentiment into positive, neutral, and negative categories. According to the evaluation results, the SVM model achieved an accuracy of 92.65%, with a precision of 0.9327, a recall of 0.9265, and an F1-score of 0.9149. Meanwhile, the NB model obtained an accuracy of 84.49%, a precision of 0.8415, a recall of 0.8449, and an F1-score of 0.8005.

These results indicate that SVM provides better performance across all evaluation metrics compared to NB. Therefore, SVM is more effective and consistent in classifying sentiments in user reviews of the Bank NTB Syariah application, although NB remains competitive and performs reasonably well on the given dataset. Based on these findings, it is recommended that the SVM model be implemented for automated sentiment analysis of Bank NTB Syariah user reviews due to its higher accuracy and consistent classification across all sentiment categories. Additionally, for future research, combining SVM with other techniques, such as deep learning or ensemble methods, could further improve the classification of underrepresented classes. Expanding the dataset and incorporating additional features, such as contextual or semantic information, may also enhance model performance and provide more comprehensive insights into user opinions.

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