

Sentiment Analysis of Digital Literacy in Society Towards Financial Technology Lending Using The Naive Bayes

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ABSTRACT

The existence of financial technology lending (pinjol), as a fintech innovation, has become a hot topic in society. Its emergence, driven by the rapid growth of the internet and ease of access to information, has a significant impact on the financial sector. Behind its convenience, this service also faces various issues due to the low digital literacy of the public. Therefore, the Financial Services Authority (OJK) uses the social media platform X (Twitter) to monitor public opinion regarding this matter. Based on this background, this research is conducted to analyze the sentiment of the Indonesian public by categorizing it into positive and negative. The text classification in this study utilizes the effective and accurate Naïve Bayes algorithm, with a dataset of 2179 tweets obtained through crawling. The implementation steps of the method include literature study, data collection, preprocessing, labeling, Naïve Bayes implementation, results, and evaluation.

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1. INTRODUCTION

Online loans, or also referred to as pinjol, are a form of innovation in the field of Financial Technology (fintech) Lending that offers convenience for the public to apply for money loans. With just an internet connection, people can apply for loans anytime and anywhere through online loan service provider websites or applications. The ease of the process and loan requirements provides potential borrowers with various options to determine the services that fit their needs [1]. Nevertheless, the decision to engage in online loans needs to be accompanied by careful consideration and accurate calculations, as there are several risks that often accompany the practice of online borrowing. One of the main issues is the lack of digital literacy and understanding among the Indonesian public regarding the negative impacts of using online loans irresponsibly. Compared to conventional loans, online loans tend to offer higher interest rates and shorter repayment terms. This raises concerns, especially regarding the high-interest rate risks that can trap users in prolonged debt and make it difficult for them to repay the loans [2][3]. The existence of online loans has sparked various controversies and issues that attract public attention [4][5]. According to data from the PASTI Task Force (Satuan Tugas Pemberantasan Aktivitas Keuangan Illegal) and the Financial Service Authority (OJK), throughout 2024, 3,240 illegal financial entities were found, of which 2,930 were illegal loan applications. Additionally, there were approximately 15,162 complaints related to illegal loans out of a total of 16,231 complaints. [6] In this case, the Financial Services Authority (OJK) supervises the development of online loans, one of which is through the social media platform Twitter, which is often used as the main platform to monitor public opinion regarding these services. Twitter is also frequently utilized as a data source in sentiment analysis [7]. Identifying the factors that trigger positive and negative sentiments towards online loan services is an important step in providing understanding and education to the public about the benefits and risks involved. In practice, sentiment analysis can be applied to various types of data such as reviews, comments, or public opinions [8]-[10].

From various research sources that use sentiment analysis, it can be found that the use of methods is very important to determine accuracy [11][12]. The Naïve Bayes method is one of the commonly used methods in sentiment analysis and has been widely applied in various similar studies. This method is known to have good accuracy and is capable of providing analysis results quickly and effectively. Among the following studies, it can be concluded that Naïve Bayes is highly recommended for the implementation of sentiment analysis, especially for research topics conducted by researchers using large data [13]-[19]

2. METHODS

The initial stage of this research is the data collection process carried out through crawling on social media platform X. The data retrieval process uses the keyword "pinjol" within the time frame from June 1, 2025, to August 31, 2025. The data crawling process is conducted using the Python programming language via Google Colab. Then the preprocessing or data processing stage is a step in the classification process aimed at cleaning and preparing the data so that it can be optimally processed in the subsequent classification stage.

2.1. Preprocessing stage

The stages are case folding for lowercase letters and characters with $\text{CaseFold}(T) = \text{lower}(T)$ (1), cleaning to remove numbers, symbols, URLs, emojis, and special characters with $\text{Clean}(T) = T - \{\text{remove everything except the words}\}$ (2), tokenizing for change the sentence to a singular word with $\text{Tokenize}(T) = [W_1, W_2, \dots, W_n]$ (3), normalization for changing

unstandardized sentences to standardized ones with Normalize (w_i) = $\{K [W_i] / [W_i], \text{if } W_i \in K, \text{if } W_i \notin K\}$ (4), stopwords removal for removing words that are not very important with Stopword(W) = $W - S$ (5), and stemming for changing the word to its base form (using Indonesian dictionary standart) with Stem(W) = $[\text{stem}(W_1), \text{stem}(W_2), \dots, \text{stem}(W_n)]$ (6).

2.2. Labeling stage

After applying preprocessing, the labeling process is continued, as illustrated in **Figure 1**. Labeling functions to facilitate the sentiment classification process, whether the review is positive or negative. Reviews with positive sentiment are labeled with the number one, while negative sentiment is labeled with zero. The formula used is Label(di) = C_j (7), di : for document or teks the- i , C_j : Class label the- j , likes : C_0 = Negative C_1 = Positive.

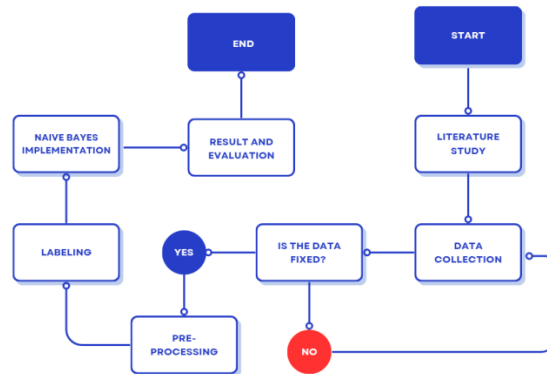


Figure 1. Research Flow

2.3. Naive Bayes Implementation stage

The last step is the implementation of naive bayes. Naïve Bayes itself is one of the classification algorithms widely used in the fields of Data Mining and Text Mining. This data consists of text that will be classified into two categories, namely text that contains sentiment. The naïve bayes algorithm works based on Bayes' theorem, which operates according to the principle of conditional probability. Conditional probability represents the likelihood or chance of an event occurring, given that another event has already occurred. Below is the formula for conditional probability.

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \quad (8)$$

The explanation of the formula is $P(A|B)$ = The probability of event A given that B has occurred, $P(B|A)$ = The probability of event B given that A has occurred, $P(A)$ = The probability of event A and $P(B)$ = The probability of event B.

2.4. Evaluation Model

In determining the best model, something is needed to measure the performance of a model so that it can be compared with one another. One way to do this is by using a confusion matrix. A confusion matrix is a table that indicates how many test data points are correctly and incorrectly classified [20]. The parameters used in the test data are TP (true positive), FN (false negative), TN (true negative), FP (false positive).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (10)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (11)$$

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (12)$$

Through the calculations above, the data will show the percentage values of each component starting from accuracy, precision, recall, and f1-score. The values represent the overall data that has gone through the training and testing process.

3. RESULTS AND DISCUSSION

3.1. Data Collection and Preprocessing

Data collected from social media X over 3 months amounted to 2179 data points. Through tweet-harvest, the collected data will be stored in .csv format to facilitate the execution of programs with Python in Google Colab. The data that has gone through the pre-processing stage will proceed to the labeling process, which is calculated from the sentiment polarity value using the sentiment method from the TextBlob object. The implementation using the following code is:

```
sentimen_percentages = (sentimen_counts / total_data) * 100.
```

From the implementation of the code above, the output percentage will appear as follows.

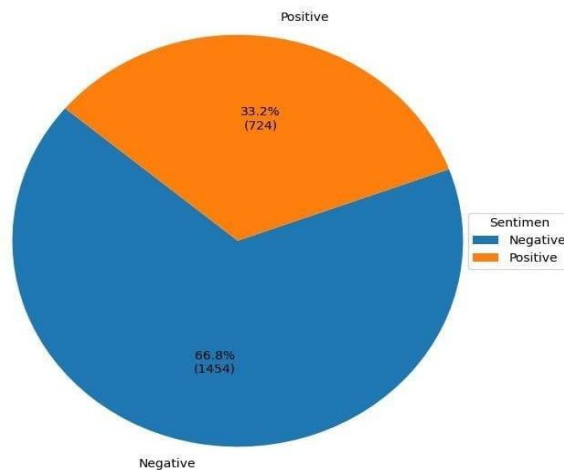


Figure 2. Output percentage

From the results above, as presented in **Figure 2**, it can be seen that the sentiment calculated using the value_count() code produces a majority of negative data. This means that the public's sentiment towards online loans has a low positive perception of 33.2 percent and a negative perception of 66.8 percent from the public. This also proves that the majority of the population is trapped in low digital literacy. Many comments indicate they are less careful about bombastic online loan offers that are often cheaper than conventional loans. However,

the reality is that bank interest rates are higher, resulting in the community becoming increasingly trapped in a more difficult economic situation.

3.2. TF-IDF Implementation, Naive Bayes and Evaluation

After determining the percentage of society through its perception, the data calculation continues with Term Frequency-Inverse Document Frequency (TF-IDF). This process repeats the tokenization process in which the weight of each root word is calculated. The result of the TF-IDF implementation is depicted in **Figure 3**.

	term		TF	TF-IDF
0	0	{ "spam": 0.1, "call": 0.1, "mengganggu": ...	{ "spam": 0.404857614376652, "call": 0.5047...	
1	1	{ "investasi": 0.1, "bodong": 0.1, "negara...	{ "investasi": 0.538357721049886, "bodong":...	
2	2	{ "wakil": 0.05263157894736842, "rakyat": 0...	{ "wakil": 0.36805342752278736, "rakyat": 0...	
3	3	{ "lindung": 0.11764705882352941, "konsumen"...	{ "lindung": 0.564210652423146, "konsumen":...	
4	4	{ "simple": 0.08333333333333333, "kurang": ...	{ "simple": 0.5249888951977512, "kurang": 0...	
...	...		...	...
2173	2173	{ "sop": 0.06666666666666667, "kantor": 0.1...	{ "sop": 0.38268347696250615, "kantor": 0.6...	
2174	2174	{ "gue": 0.1, "gapeduli": 0.1, "gaya": 0....	{ "gue": 0.26957297167141697, "gapeduli": 0...	
2175	2175	{ "nyokap": 0.09090909090909091, "tau": 0.0...	{ "nyokap": 0.4525556456718814, "tau": 0.24...	
2176	2176	{ "jual": 0.125, "buku": 0.0625, "bekas":...	{ "jual": 0.5356206152288437, "buku": 0.368...	
2177	2177	{ "galbay": 0.125, "panjul": 0.125, "paspo...	{ "galbay": 0.3654985460868937, "panjul": 0...	

Figure 3. TF-IDF result

After that, the data above will be separated into training data and test data. Based on the processed data, it will be divided with a proportion of 70% for training data and 30% for test data. Using `X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=654)`. Continue the implementation of naive bayes using `nb_classifier = MultinomialNB() nb_classifier.fit(X_train_tfidf, y_train)`. And the evaluation ended with the use of a confusion matrix, the results are as follows:

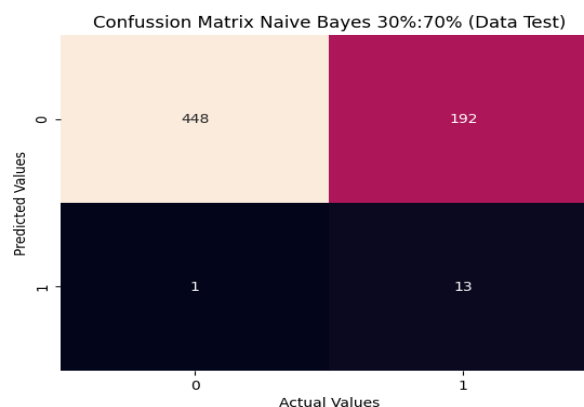


Figure 4. Confusion Matrix result

Based on **Figure 4**, there are 13 positive data accurately predicted as positive, 192 positive data incorrectly predicted as negative, 448 negative data accurately predicted as negative, and 1 negative data incorrectly predicted as positive. The results are then evaluated using a classification report as shown in **Table 1**.

Table 1. Naive Bayes result

	Precision	Recall	F1-Score	Report
Negative	0,70	1,00	0,82	449
Positive	0,93	0,06	0,12	205
Accuracy			0,70	654
Macro Avg	0,81	0,53	0,47	654
Weighted Avg	0,77	0,70	0,60	654

The data above shows the classification report results from the Naïve Bayes algorithm using 30% of the test data from a total of 2,185 tweets, which amounts to 654 data points. Based on this evaluation, the precision is obtained at 93%, the recall at 6%, the f1-score at 12%, and the accuracy reaching 70% in this test.

To facilitate the observation of the data, barplot and wordcloud visualizations are used. The visualizations will depict both positive and negative sentiments that illustrate the frequency or occurrence of related words. Below are the results of the visualizations:

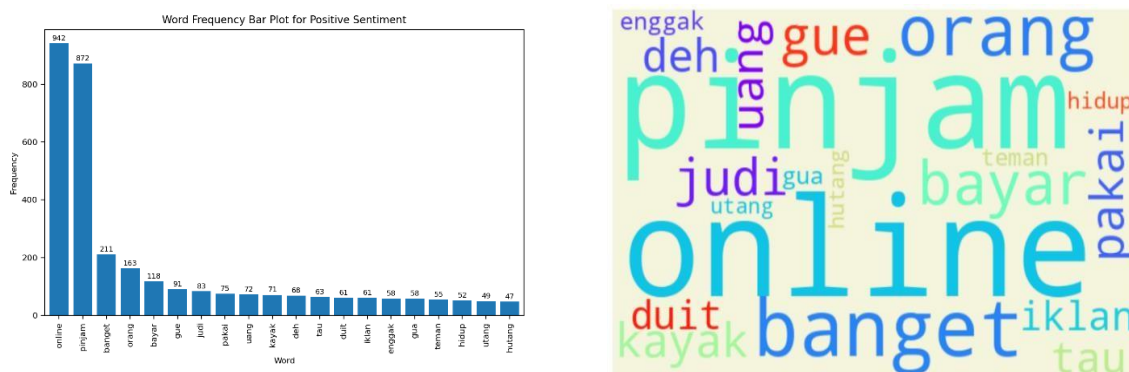


Figure 5. Barplot and wordcloud of positive sentiment

Based on **Figure 5**, several words that appear most frequently are obtained, such as the word "online" with a frequency of 942 times, the word "pinjam" 872 times, "banget" 211 times, and so on. This data shows supportive words or additional expressions in sentences with a positive sentiment. Of the 33.2 percent of sentences identified as positive, the public still uses the list of words above to express sentences related to online loans.

Meanwhile, as depicted in **Figure 6**, there are also several words that appear most frequently, such as the word "online" with a frequency of 1866 times, the word "pinjam" 1727 times, "bayar" 274 times, and so on. The words that appear are those that have negative sentiment and are the most frequently discussed topics by users. In the list of words above, it can also be analyzed that the word 'lilit' is in the negative sentiment category and certainly is not in the positive sentiment list. In addition, the words 'bayar' and 'judi', although they are also in the positive sentiment list, have a clearly larger and more significant percentage in negative sentiment.

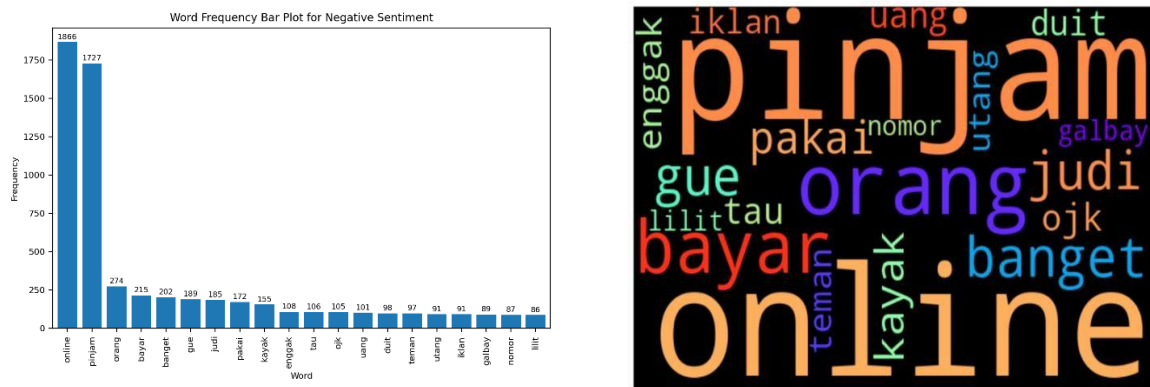


Figure 6. Barplot and wordcloud of negative sentiment

Words of larger size in the wordcloud indicate that these words appear more frequently and are part of the discussion topic for both positive and negative assessments by users.

4. CONCLUSION

This research uses the Naïve Bayes algorithm to classify sentiment towards online loans on social media X. The analysis results show that the majority of public sentiment is negative with a percentage of 66.8% and positive at 33.4%. Evaluation using a confusion matrix indicates a Naïve Bayes accuracy of 70% on a 30:70 data split. For the implementation of bar plots and word clouds, both positive and negative sentiments show that the words borrow, online, people, and gambling are among the top list of words frequently used by users to express in sentence form.

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6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

REFERENCES

- [1] Ramdani, B., Saputra, A. D., Rafli, M., & Zahir, A. (2024). Analisis Sentimen Terhadap Ulasan Aplikasi Pinjaman Online (PINJOL) di Google Play Store Menggunakan Naive Baiyes Classifier. *Jurnal Riset Informatika dan Teknologi Informasi*. 1(2), 61–64.
- [2] Kusuma, F. W., Dermawan, P., Samsie, I., & Salman, N. (2024). Tinjauan Sentimen Terhadap Ulasan Aplikasi Peminjaman Online Dengan Metode Support Vector Machine (SVM). *MALCOM: Indonesian Journal of Machine Learning and Computer Science* 4(1), 13–21.
- [3] Wijayanti, S. (2022). Dampak Aplikasi Pinjaman Online Terhadap Kebutuhan Dan Gaya Hidup Konsumtif Buruh Pabrik. *MIZANIA: Jurnal Ekonomi dan Akuntansi*, 2(2), 230-235.
- [4] Arvante, J. Z. Y. (2022). Dampak Permasalahan Pinjaman Online dan Perlindungan Hukum Bagi Konsumen Pinjaman Online. *Ikatan Penulis Mahasiswa Hukum Indonesia Law Journal*, 2(1), 73-87.

- [5] Sugangga, R., and Sentoso, E. H. (2020). Perlindungan Hukum Terhadap Pengguna Pinjaman Online (Pinjol) Ilegal. *Pakuan Justice Journal of Law*, 1(1), 47-61.
- [6] ANTARA, J. (2025). *OJK: Pinjol ilegal jadi kasus paling banyak ditemukan SatgasPASTI*. Jakarta (ANTARA). <https://www.antaranews.com/berita/4663565/ojk-pinjol-ilegal-jadi-kasus-paling-banyak-ditemukan-satgas-pasti>
- [7] Ismail, A. R., and Hakim, R. B. F. (2023). Implementasi Lexicon Based Untuk Analisis Sentimen Dalam Mengetahui Trend Wisata Pantai Di DI Yogyakarta Berdasarkan Data Twitter. *Emerging Statistics and Data Science Journal*, 1(1), 37-45.
- [8] Medhat, W., Hassan, A., and Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, 5(4), 1093-1113.
- [9] Utami, D. S., and Erfina, A. (2021). *Analisis Sentimen Pinjaman Online Di Twitter Menggunakan Algoritma Support Vector Machine (SVM)*. 299–305.
- [10] Munna, A., and Zuliarso, E. (2024). Interpretasi model Stacking Ensemble untuk analisis sentimen ulasan aplikasi pinjaman online menggunakan LIME. *AITI: Jurnal Teknologi Informasi*, 21(2), 183–196.
- [11] Awangga, R. M., and Khonsa, N. H. (2022). Analisis Performa Algoritma Random Forest dan Naive Bayes Multinomial pada Dataset Ulasan Obat dan Ulasan Film. *InComTech: Jurnal Telekomunikasi dan Komputer*. 12(1), 60–70.
- [12] Mualfah, D., Prihatin, A., and Firdaus, R. (2023). Analisis Sentimen Masyarakat Terhadap Kasus Pembobolan Data Nasabah Bank BSI Pada Twitter Menggunakan Metode Random Forest Dan Naïve Bayes. *Jurnal FASILKOM (Teknologi Informasi Dan Ilmu Komputer)* 13(3), 614–620.
- [13] Miranda, K., and Suryono, R. R. (2025). Analisis Sentimen Pinjaman Online: Studi Komparatif Algoritma Naïve Bayes, Decision Tree, dan KNN. *Edumatic: Jurnal Pendidikan Informatika*, 9(2), 372-381.
- [14] Siki, Y. C. H., Tokan, T. B. A., Manehat, D. J., Ngaga, E., and Mau, S. D. B. (2025). Perbandingan Metode Naïve Bayes dan K-Nearest Neighbor Terhadap Sentimen Analisis Pinjaman Online. *Jurnal Media Informatika*, 6(3), 1614-1622.
- [15] Ghozali, M. I., Sugiharto, W. H., and Iskandar, A. F. (2023). Analisis Sentimen Pinjaman Online Di Media Sosial Twitter Menggunakan Metode Naive Bayes. *KLIK: Kajian Ilmiah Informatika Dan Komputer* 3(6), 1340–1348. <https://doi.org/10.30865/klik.v3i6.936>
- [16] Miftahusalam, A., Pratiwi, H., and Slamet, I. (2023). Perbandingan Metode Random Forest dan Naive Bayes pada Analisis Sentimen Review Aplikasi BCA Mobile. *SIPTEK : Seminar Nasional Inovasi dan Pengembangan Teknologi Pendidikan*, 1–8.
- [17] Huda, M. M., Tricahyo, V. A., Yusron, R. D. R., and Septarina, A. A. (2024). Analisis Tingkat Literasi Digital Siswa Berbasis Web Game Edukasi Sebagai Bagian Kesiapan Pembelajaran Digital. *Jurnal Sistem Informasi dan Teknologi Informasi Komputer*. 2(6), 85-97. <https://doi.org/10.53624/jsitik.v2i2.352>
- [18] Rieuwpassa, J. A., Sugito, and Widiari, T. (2023). Implementasi Metode Naive Bayes Classifier Untuk Klasifikasi Sentimen Ulasan Pengguna Aplikasi Netflix Pada Google Play. *Jurnal Gaussian*, 12(3), 362-371. <https://doi.org/10.14710/j.gauss.12.3.362-371>
- [19] Yanto, A. F. A., and Testiana, G. (2024). Implementasi Metode Klasifikasi Naïve Bayes Untuk Memprediksi Juara La Liga. *Jurnal Teknologi Sistem Informasi*, 5(2). <https://doi.org/10.35957/jtsi.v5i2.8028>
- [20] Tharwat, A. (2021). Classification assessment methods. *Applied Computing and Informatics*, 17(1), 168-192.