Indonesian Journal of Artificial Intelligence and Data Mining (IJAIDM)
Vol. 8, No. 2, July 2025, pp. 448 – 458
p-ISSN: 2614-3372 | e-ISSN: 2614-6150

Sentiment Analysis of BCA Mobile App Reviews Using K-Nearest Neighbour and Support Vector Machine Algorithm

[1]Yosefin Yuniati Zandroto, [2*]Anik Vega Vitianingsih, [3]Anastasia Lidya Maukar, [4]Nina Kurnia Hikmawati, [5]Rusdi Hamidan
[1,2,5]Informatics Departement, Universitas Dr. Soetomo, Surabaya, Indonesia
[3]Industrial Engineering Department, President University, Bekasi, Indonesia
[4]Information System Department, Universitas Komputer Indonesia, Indonesia
Email: [1]yosefinyzand@gmail.com, [2]vega@unitomo.ac.id, [3]almaukar@president.ac.id, [4]ninakaha@email.unikom.ac.id, [5]rusdi@unitomo.ac.id

Article Info

Article history:
Received Jun 13th, 2025
Revised Jul 6th, 2025
Accepted Jul 30th, 2025

Keyword:
BCA Mobile
K-Nearest Neighbour
Lexicon-Based
Machine Learning
Sentiment Analysis
Support Vector Machine

ABSTRACT

The rapid evolution of digital technology has significantly transformed the financial services landscape, especially in the realm of mobile banking. BCA Mobile stands among the most popular apps for digital banking in Indonesia. Despite its widespread adoption, user reviews reflect diverse viewpoints and sentiments about the app. The objective of this research is to examine the user sentiments regarding the BCA Mobile app, based on reviews sourced from the Google Play Store and App Store. Two classification models, namely Support Vector Machine (SVM) and K-Nearest Neighbour (K-NN), are used in the analysis process. The collected review data undergoes several pre-processing stages and is labeled automatically using a Lexicon-Based technique. For feature weighting, the TF-IDF (Term Frequency-Inverse Document Frequency) approach is used.. Sentiment classification is then carried out using both K-NN and SVM, with performance evaluated through a matrix of confusion based on measurements like F1-score, recall, accuracy, and precision. The findings show that the SVM algorithm outperforms K-NN in terms of performance, with an accuracy of 94%, while K-NN achieves an accuracy of 82%. This study offers valuable insights for BCA management in understanding user sentiment and enhancing service quality through the application of artificial intelligence.

Corresponding Author :
Anik Vega Vitianingsih
Informatics Department, Universitas Dr. Soetomo
Semolowaro Street No.84, Menur Pumpungan, Sukolilo District, Surabaya, East Java 60118
Email: vega@unitomo.ac.id

DOI: http://dx.doi.org/10.24014/ijaidm.v8i2.37773

1. INTRODUCTION

The swift evolution of information and communication technologies has significantly impacted numerous industries, with the financial sector being among the most affected [1]. One of the most transformative innovations in this domain is mobile banking, which allows users to conduct transactions conveniently through smartphones [2]. In Indonesia, BCA Mobile is one of the most widely used mobile banking applications, with over 10 million downloads and a rating of 4.5 stars on the Google Play Store [3]. Its popularity stems from its diverse features and user-friendly interface. Nevertheless, despite its widespread adoption, user reviews reveal a wide spectrum of opinions ranging from satisfaction with ease of access to complaints about technical glitches, difficult navigation, and security issues.

To explore these varied user experiences, analyzing online reviews proves crucial in uncovering public opinion and gauging satisfaction levels. Such analysis enables financial institutions like Bank Central Asia (BCA) to better understand user expectations and continually improve their services [4][5]. Prior studies in this area have applied several text classification approaches and datasets. For example, research using Twitter data has implemented algorithms such as Naïve Bayes, Lexicon-Based methods, and LDA Topic

Modeling, with pre-processing stages that include filtering, case folding, normalization, tokenization, stopword removal, and stemming [6]. These studies evaluated performance using confusion matrices and metrics like accuracy, recall, and precision. Another study based on Google Play Store reviews applied Naïve Bayes, Random Forest, and Logistic Regression, achieving an F1-score of 81%, 82% recall, 84% precision, and 82% accuracy [7].

Further research involving mobile banking feedback employed the Naïve Bayes algorithm and achieved a classification accuracy of 85.31% for both positive and negative sentiments [8]. Meanwhile, a study utilizing the SVM algorithm alongside pre-processing steps like punctuation removal and stemming reported results of 87.31% precision, 85.87% accuracy, and 86.96% recall [9]. However, in a study comparing Naïve Bayes performance using a 60:40 training-testing split, accuracy was only 71.03% despite high precision (97.67%), indicating an imbalance in the dataset. This imbalance is reflected in the recall rate of just 33.60%, with a dominance of negative sentiments (396 instances) over positive ones (312) [10] These findings highlight that although methods such as Naïve Bayes and SVM are frequently used, direct comparisons between Support Vector Machine (SVM) and K-Nearest Neighbour (K-NN) particularly on datasets derived from both the Google Play Store and App Store for BCA Mobile remain limited [11].

To address this research gap, the present study proposes a comparative evaluation of K-NN and SVM for classifying user sentiment toward BCA Mobile. The classification process is preceded by Lexicon-Based sentiment labeling. Data is collected via web scraping of user reviews posted between 2023 and 2025 on both the Google Play Store and App Store platforms. The pre-processing pipeline includes data cleaning, case folding, tokenization, stopword removal, and stemming. Term weighting is performed using the Term Frequency-Inverse Document Frequency (TF-IDF) method, while the sentiment classification itself is executed using both K-NN and SVM algorithms. Performance evaluation is conducted through confusion matrix analysis and metrics such as accuracy, precision, recall, and F1-score. By comparing these two algorithms, this study aims to uncover which model better captures user sentiment, considering their algorithmic differences K-NN being a distance-based classifier and SVM a margin-based one. The results are expected to provide insights for improving mobile banking services and contribute to the growing body of research on sentiment classification in digital financial platforms.

2. RESEARCH METHODOLOGY

This analysis aims to evaluate and compare the effectiveness of K-NN and SVM in identifying user sentiment related to the BCA Mobile application. The evaluations analyzed reflect users' perceptions of the application's features, performance, and user experience. The primary aim of this investigation is to ascertain which algorithm yields the highest classification accuracy in sentiment classification using user review datasets. The process undertaken in this research is outlined step by step in Figure 1.

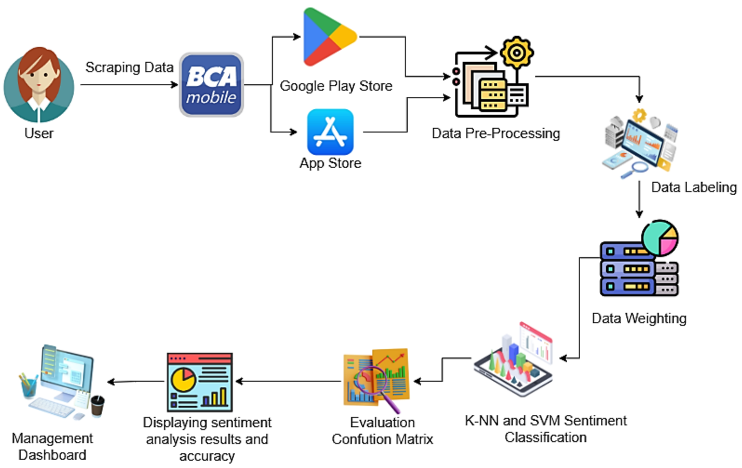


Figure 1. Research Proses Design

The initial stage of the research began with data collection using web scraping, sourced from the Google Play Store and App Store review platforms. The collected data consisted of user reviews in Indonesian text, reflecting users' opinions and experiences with the BCA Mobile application. Next, the review data entered the pre-processing stage, which consisted of five main steps: Tokenization, Cleaning, Case Folding, Stopword Elimination, and Stemming. After this, the data was labeled using a Lexicon-Based approach, where each review was assigned a sentiment label (positive, negative, or neutral) based on a predefined dictionary of sentiment-bearing words. This approach is widely used due to its interpretability and simplicity, particularly in domains where labeled data is scarce. Following the labeling stage, the TF-IDF technique was applied to extract features. TF-IDF helps identify significant terms in a document by calculating the importance of words relative to the entire corpus, and has been effectively used in various sentiment analysis tasks

After feature extraction, two classification models were applied:

1. SVM is a supervised learning model that constructs a hyperplane to separate classes and has shown strong performance in text classification due to its ability to handle high-dimensional data.
2. K-NN is a distance-based classifier that determines the sentiment of a new review based on the majority sentiment among its nearest neighbors in the training set. Its simplicity and non-parametric nature make it a popular baseline in sentiment classification.

The classification results were evaluated using a Confusion Matrix, which includes four performance indicators: accuracy, precision, recall, and F1-score. These metrics were used to determine which algorithm provides better performance in classifying user sentiment. The novelty of this research lies in the comparative analysis of SVM and K-NN using user reviews written in Bahasa Indonesia, collected from both the Google Play Store and the App Store for the BCA Mobile application. While prior research often focuses on a single platform or uses English-language data, this study explores real-world user sentiment across multiple platforms and time periods (2023–2025), providing updated insights into Indonesian users' experiences with mobile banking applications.

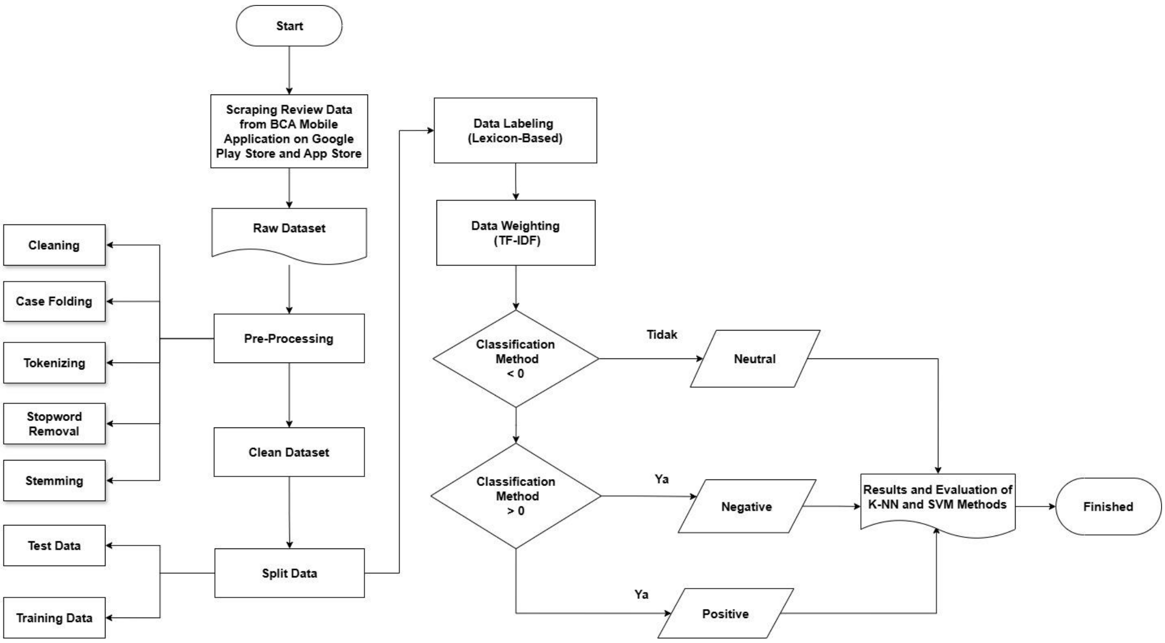


Figure 2. Proses of Algorithm

Figure 2 illustrates the algorithm's process flow in this study, which begins with obtaining datasets by using user web scraping comments available in the Google Play Store and App Store platforms. This raw dataset is then passed through a preliminary processing phase that includes Tokenising, cleaning, case folding, removing stopwords, and stemming. After pre-processing, the cleaned data is partitioned into test and training sets. The next step involves applying the TF-IDF method for feature weighting, followed by data annotation using a Lexicon-Based approach. The K-NN and SVM algorithms are used to carry out the classification procedure. If the classification score is > 0, the review is categorized as positive. If not, it will be checked whether the score <0 to be classified as negative, and if not, it is categorized as neutral. The classification results of these two algorithms are visualized in the form of diagrams or graphs, and the performance of each method is evaluated through a comprehensive analysis. The process ends at the system results and conclusions stage.

2.1. Data Collection

This research utilized data gathered from reviews of the BCA Mobile application, available on two digital app platforms, Google Play Store and App Store, during the period from 2023 to 2025. These reviews reflect users' opinions and experiences with the application's features, performance, and service quality. The process of obtaining the data employed web scraping techniques, a method for automatically extracting information from web pages. The scraping process was carried out using a programming approach using Python, utilizing libraries such as BeautifulSoup, Selenium, and Pandas. A total of 1,001 reviews were successfully collected, sourced from 1,001 entries on Google Play and 1,118 user reviews on the App Store, which were then saved in comma-separated values (.csv) format to facilitate further analysis during the pre-processing, sentiment labeling, and classification stages.

2.2. Pre-Processing Data

Raw datasets obtained through scraping require data pre-processing because they typically still contain various irrelevant elements, such as special characters, excess spaces, non-standard words, and information that does not support analysis. If the data is not cleaned first, the analysis process may produce inaccurate outcomes that don't accurately represent the real conditions [12]. Therefore, Pre-processing data is an important precede by step preceding the sentiment step of classification. The following are the stages of data pre-processing:

1. Data Cleaning: This process aims to remove symbols, numbers, punctuation marks, emojis, and other irrelevant elements from the review text, thereby ensuring cleaner and more focused analysis results [13].
2. Data Case Folding: Converting all letters to lowercase to avoid differences between words and reduce complexity [14].
3. Data Tokenization: The process of breaking down text into individual words [15].
4. Stopword Removal: Eliminating frequently used words that do not contribute significant meaning to the text [16].
5. Stemming: A technique that reduces refining words down to their root structure through the removal of added parts attached to them [17].

2.3. Labeling Data

Once the initial pre-processing is finalized, the following stage involves categorizing user evaluations into three sentiment types: positive, neutral, and negative. This grouping is performed automatically using a Lexicon-based methodology, which utilizes a dictionary containing a list of words and their respective sentiment values. A score is given to each word in the text based on its polarity, which is positive>0, negative<0, and neutral. The final review score is obtained by summing the sentiment values of all words that show up in the text [18]. The results of this calculation are used for assigning a sentiment classification to the evaluation. If the evaluation receives a score of 0, it is considered neutral. If it's less than zero, it is classified as negative. If it is greater than zero, it is categorized as positive. This calculation using Equation (1)

$$(s_i) = \sum_{i=1}^{n} \quad \text{Sentimen}\ (\omega_i) \tag{1}$$

Through this approach, the labeling process can be run automatically and consistently, without the need for time-consuming manual annotation [19]. Following labelling completion, the dataset is weighted using the TF-IDF technique and then classified using the SVM and K-NN models. The performance of both models is analysed using important metrics like accuracy, precision, recall, and F1-score, as well as a confusion matrix.

2.4. Word Wighting

This study employs as a feature extraction method, the TF-IDF methodology assesses the significance of every word in a document. By assigning it a weight based on its frequency [20]. The weight is calculated from the term's repetition within one document and its uncommon presence in the broader collection (corpus) [20]. Words that consistently appear in one document but are rarely found in others are assigned higher TF-IDF scores, as they are regarded as more representative of the document's content, using Equation (2). Conversely, words that frequently appear in many documents will receive a lower weight because they are considered less specific in terms of information.

$$\text{TF} - \text{IDF}(t, d) = \text{TF}(t, d)\ x\ \ \text{IDF}\ (t) \tag{2}$$

2.5. Analysis Model

Following the feature weighting phase, the categorization procedure is carried out using K-NN and SVM algorithms. Both methods are applied independently to identify which algorithm yields the greatest degree of categorization precision.

1. K-Nearest Neighbours (K-NN)
   K-NN refers to a machine learning approach used for classification and regression tasks [21]. This method determines the class of a data point by examining the most votes from the K nearest neighboring data points, which are determined based on a specific distance calculation [22]. In this study, the distance between data is calculated using the Cosine Similarity method [23]. This technique assesses the level of similarity of two vectors based on the size of the angle between them. The smaller the angle formed, the greater the cosine value, showing that the two vectors have a higher degree of similarity. The calculation of Cosine Similarity can be seen in Equation (3).

$$\cos(\theta) = \frac{\Sigma_{n=1}^{n} A_n \cdot B_n}{\sqrt{\sum_{n=1}^{n} A_n^2} \cdot \sqrt{\Sigma_{n=1}^{n} B_n^2}} \quad (3)$$

2. Support Vector Machine (SVM)
   SVM is a member of the category of supervised learning models that aim to solve classification and regression tasks efficiently [24]. The central purpose of SVM is to draw a hyperplane that can clearly and widely differentiate two sets of data. The larger the margin between classes, the better the model's generalization [25]. To handle data that cannot be separated linearly, SVM employs a kernel function (also known as the kernel trick) to convert the data into a feature space with more dimensions, thereby allowing for linear separation in that space. The mathematical formulation of SVM is presented in Equation (4).

$$f(x) = w \cdot x + b \quad (4)$$

2.6. Evaluation

Model evaluation is a crucial part of the classification process in machine learning, as it gauges how well the model works. Accurately predicts data labels. One of the most frequently used evaluation methods is the Confusion Matrix [26], which Describes the effectiveness of a categorization model by contrasting the actual labels of the test data with the anticipated outcomes. The Confusion Matrix consists of four main components, namely:

$$\text{Akurasi} : \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (5)$$

$$\text{Presisi} = \frac{(TP)}{(TP+FP)} \quad (6)$$

$$\text{Recall} = \frac{(TP)}{(TP+FN)} \quad (7)$$

$$F1-\text{Score} = 2 \text{ x } \frac{(\text{Presisi x Recall})}{(\text{Presisi+Recall})} \quad (8)$$

3. RESULTS AND ANALYSIS

This study successfully collected 1,001 comments from users on the Google Play Store and 1,118 from the App Store using web scraping techniques. The data was gathered using various relevant keywords and phrases, such as "BCA", "BCA Mobile", "m-banking BCA", and other terms related to user experience with BCA's digital banking services. The collected reviews reflect several key aspects, including ease of use, transaction speed, system stability, and the effectiveness of available features. Table 1 presents selected examples of the scraped reviews used in the sentiment analysis process.

Table 1. Datasets

Example Comment Data from Google Play Store Dataset
applikasi Sangat membantu sekali, bila ganti nomor tidak perlu ke bank terdekat, gk seperti app syari'ah nya
login susah bgt, udah isi pulsa sms berkali kali sampe pulsa habis masih belum bisa
pelayanan sangat memuaskan, para staf jg sangat respon dan baik ramah. Bca ☆☆☆☆☆
baru saja instal ulang m banking. untuk login gagal terus
Example Comment Data From App Store Dataset
Apk nya keren dan fiturnya sangat mudah dimengerti
gak bisa diupdate, padahal sudah test pakai wifi maupun paket data pribadi
Verifikasi datanya sangat buruk, sudah masukan data yang benar sesuai instruksi tapi verifikasi tetap gagal. Harus diperbaiki!

Bca plis jangan terlalu sering update, pengguna ios versi lama yg sudah tidak bisa update ios jadi kesulitan, apalagi mbanking itu penting banget kalo ga bisa update masa ga bisa di gunain, lagipula tidak ada yg perlu di perbaiki lagi, versi baru dan lama sama saja

3.1. Data Pre-Processing

Once data collection is finalized, Preparation is done to improve the caliber of representation in the dataset. The sequence of pre-processing steps is illustrated in Table 2.

Table 2. Pre-Processing

Result Google Play Store	
pelayanan sangat memuaskan, para staf jg sangat respon dan baik ramah. Bca ☆☆☆☆☆	
Cleaning	pelayanan sangat memuaskan para staf jg sangat respon dan baik ramah bca
Case Folding	pelayanan sangat memuaskan para staf jg sangat respon dan baik ramah bca
Tokenizing	["pelayanan", "sangat", "memuaskan", "para", "staf", "jg", "sangat", "respon", "dan", "baik", "ramah", "bca"]
Stopword Removal	["pelayanan", "memuaskan", "staf", "respon", "baik", "ramah", "bca"]
Stemming	["layan", "puas", "staf", "respon", "baik", "ramah", "bca"]
Result App Store	
Apk nya keren dan fiturnya sangat mudah dimengerti	
Cleaning	Apk nya keren dan fiturnya sangat mudah dimengerti
Case Folding	apk nya keren dan fiturnya sangat mudah dimengerti
Tokenizing	["apk", "nya", "keren", "dan", "fiturnya", "sangat", "mudah", "dimengerti"]
Stopword Removal	["apk", "keren", "fitur", "mudah", "dimengerti"]
Stemming	["apk", "keren", "fitur", "mudah", "ngerti"]

3.2. Labeling Data

The data labeling process is performed automatically using a lexicon-based approach, where every word in the review has a score based on a sentiment dictionary. The total of each review is determined by summing the sentiment values of each word. The classification criteria are as follows: If the score If higher than zero, the evaluation is categorized as positive. A review is categorized as negative if the score is less than zero. The review is categorized as impartial if the score is zero. The outcomes of the data labeling procedure are displayed in Table 3.

Table 3. Labeling Datasets

Google Play Store Clean Dataset Text	Score	Sentiment
["layan", "puas", "staf", "respon", "baik", "ramah", "bca"]	3	Positif
App Store Clean Dataset Text	Score	Sentiment
["apk", "keren", "fitur", "mudah", "ngerti"]	3	Positif

3.3. Word Weighting

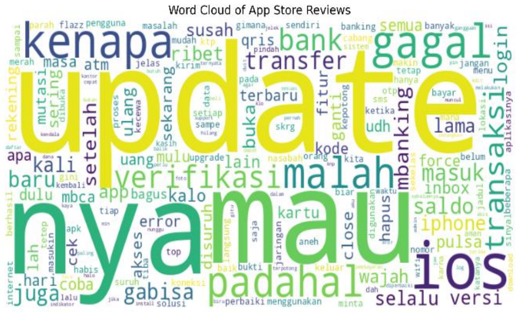
Once Labels have been applied to the data, the feature extraction process uses the TF-IDF method, which calculates word weights by considering the frequency of a term within an individual document and its infrequency across the entire corpus. Table 4 shows the results of TF-IDF feature extraction.

Table 4. Weighting Result Google Play End App Store

Google Play Store		App Store	
Teks	TF-IDF	Teks	TF-IDF
layan	0.378	Apk	0.447
puas	0.378	Fitur	0.447
staf	0.378	Keren	0.447
Respon	0.378	Mudah	0.447
Baik	0.378		
Ramah	0.378		
bca	0.378		

Figure 3 illustrates the weighting stage using the TF-IDF method. The next step is to combine the weights of each word to identify the most dominant words in each sentiment category. This aggregation process identifies words with the highest weights that reflect sentiments classified as neutral, negative, or positive. The final result of this aggregation is visualized in the form of a WordCloud, where words with the highest weights appear more prominently. This visualization aims to facilitate the analysis of sentiment characteristics in user reviews. The WordCloud is created separately for two data sources, Google Play and the App Store, allowing word patterns from each platform to be visually compared. Figure 3. WordCloud visualization of Google Play and App Store reviews.

(a) Google Play Store



(b) App Store

Figure 3. Word Cloud Apps

3.4. Evaluation Model

This phase involves assessing the classification models to determine how effectively they categorize the data. The evaluation is carried out utilizing performance measures such as accuracy, precision, recall, and F1-score, as presented in Table 3, to compare the overall effectiveness of the K-NN and SVM algorithms.

Table 5. Evaluation

Matrix	K-NN	SVM
Accuracy	0.82	0.94
Precision	0.80	0.94
Recall	0.82	0.94
F1-Score	0.78	0.93

To assess the two classification systems' performance, a Confusion Matrix was utilized as an evaluation tool to present detailed accuracy results. It outlines the proportion of correct and incorrect predictions for each class, offering a clearer picture of model performance. In this research, the Confusion Matrix was used to visualize how well the K-NN and SVM algorithms classified sentiment. Figure 4 presents a side-by-side comparison of their confusion matrices.

The results demonstrate that the SVM algorithm outperformed K-NN across all metrics. This performance difference can be attributed to several factors:

1. SVM is particularly effective in handling high-dimensional and sparse data, which is typical when using TF-IDF representations in text classification tasks. Its ability to construct an optimal hyperplane makes it more robust in distinguishing between sentiment classes in such contexts.
2. In contrast, K-NN relies heavily on distance calculations, which can become less reliable in high-dimensional spaces due to the "curse of dimensionality." This may lead to less accurate neighbor comparisons and consequently weaker performance.
3. Furthermore, K-NN is sensitive to noise and outliers, and its performance can degrade when irrelevant or redundant features exist—which is often the case in raw text data, even after preprocessing.

Figure 4 illustrates the confusion matrices for both K-NN and SVM models, highlighting the classification performance for the three sentiment classes: negative, neutral, and positive.

1. K-NN Confusion Matrix Analysis:
    a. Neutral sentiment: 140 reviews were correctly classified as neutral.
    b. Positive sentiment: Out of 48 actual positive reviews, only 24 were correctly classified. The other 24 were misclassified as neutral.
    c. Negative sentiment: K-NN failed to correctly classify any negative reviews. All 12 negative reviews were misclassified as neutral.
    d. Pattern observed: The model demonstrates a clear bias toward the neutral class, often misclassifying both positive and negative reviews as neutral. This suggests that K-NN may struggle to distinguish sentiment polarity when review text features are.

2. SVM Confusion Matrix Analysis:
    a. Neutral sentiment: 132 reviews were correctly predicted as neutral; 8 were misclassified as positive.

b. Positive sentiment: Out of 48 positive reviews, 44 were correctly classified, with only 4 misclassified as neutral.
c. Negative sentiment: 6 reviews were correctly identified as negative, and 6 were misclassified as positive.
d. Pattern observed: SVM shows a more balanced distribution of predictions, with much better accuracy in identifying both positive and negative sentiments. Although a few neutral reviews were misclassified as positive, and vice versa for negative, the overall classification is more accurate and less biased than K-NN.

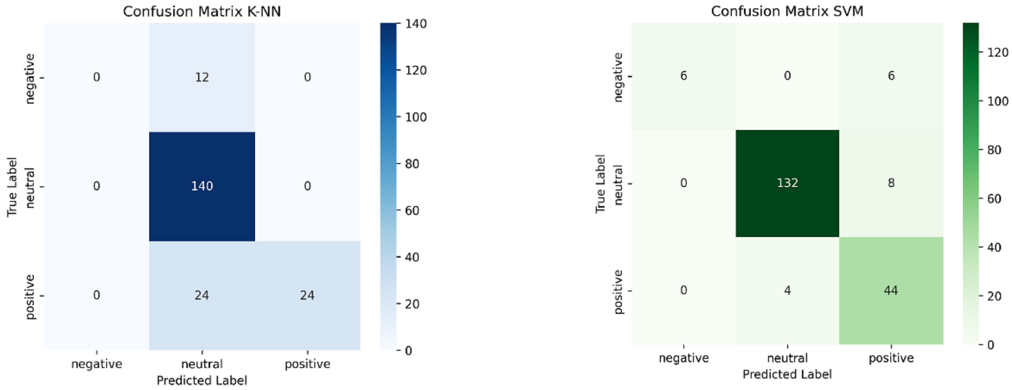


Figure 4. Confusion Matrix Model

A performance analysis comparing the K-NN and SVM model algorithms is visualized using bar charts to facilitate the interpretation of the results, which can be seen in Figure 5. This visualization offers a detailed understanding of how well each method performs in data classification. By examining the diagram, one can determine the distribution of predictions from each algorithm, thus enabling the evaluation of how accurate and generalizable each model is. Figure 5 clearly illustrates a performance comparison between the K-NN and SVM models across four evaluation metrics: accuracy, precision, recall, and F1-score. In all metrics, the SVM algorithm significantly outperforms K-NN. The most notable performance gap is observed in the F1-score (0.93 for SVM vs. 0.78 for K-NN), indicating that SVM performs more consistently in balancing both precision and recall. Additionally, SVM achieves equal precision and recall (0.94), suggesting strong stability without trade-offs between identifying true positives and avoiding false positives. Meanwhile, K-NN shows lower and slightly imbalanced scores, with precision at 0.80 and recall at 0.82.

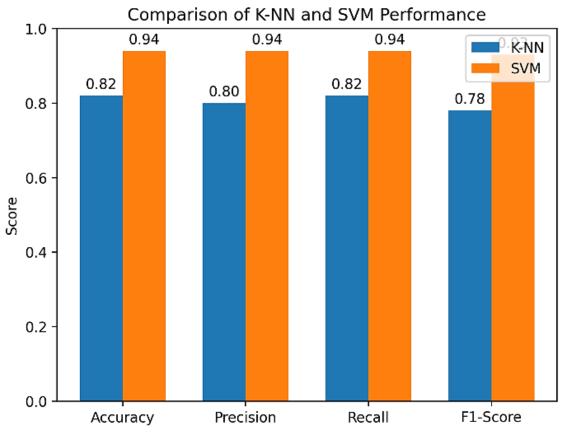


Figure 5. Comparison of K-NN and SVM Model Performance

3.5. Discussions

The results of this study show that the SVM algorithm consistently outperformed the K-NN algorithm across all evaluation metrics—accuracy, precision, recall, and F1-score. This outcome reinforces the capability of SVM in handling high-dimensional and sparse data, such as text features extracted using TF-IDF, while also highlighting the limitations of K-NN in such contexts due to its sensitivity to noise and reliance on distance-based calculations. These findings are consistent with those of Putri et al. [5], who also found that SVM outperformed K-NN in classifying sentiment related to brand ambassador influence.

Similarly, Nurmalasari et al. [11] reported that SVM provided better accuracy and general performance than K-NN and Naïve Bayes in sentiment classification tasks. Moreover, Ranataru and Trianasari [2] emphasized the suitability of SVM for sentiment analysis in Bahasa Indonesia, particularly within the mobile banking domain, which aligns closely with the context of this study involving BCA Mobile. By comparing the performance of SVM and K-NN using user reviews collected from multiple platforms over the 2023–2025 period, this study not only supports previous research but also expands its scope. It demonstrates the robustness of SVM in real-world sentiment analysis tasks, particularly when dealing with diverse and multilingual datasets in the financial technology sector.

4. CONCLUSION

This research performed a sentiment classification study of user evaluations for the BCA Mobile application sourced from the Google Play Store and App Store, employing the K-NN and SVM algorithms. The evaluation findings indicate that the SVM algorithm outperformed K-NN, achieving an accuracy of 94%, precision of 94%, and recall of 94%, culminating in an F1-score of 93%. The K-NN approach achieved an accuracy of 82%, a precision of 80%, a recall of 82%, and an F1-score of 78%. Sentiment analysis reveals that most user reviews exhibit positive sentiment, indicating a high level of satisfaction with the BCA Mobile app. Words that appear in positive reviews are often related to the ease of use and efficiency of the app's features in supporting banking transactions. Hence, it can be inferred that the SVM method provides enhanced accuracy and efficiency in categorizing the sentiment expressed in reviews of the BCA Mobile app. For further research, it is recommended that this approach be developed by testing other machine learning techniques or using ensemble methods to improve classification. Additionally, handling imbalanced data can also be applied to enhance the overall performance of the model.

REFERENCES

[1] Zahrotul Hayat and Syamsul Hidayat, "Analisis Kepuasan Pelayanan Penggunaan Mobile Banking BCA," Jurnal Manajemen Riset Inovasi, vol. 2, no. 2, pp. 261–268, Jan. 2024, doi: 10.55606/mri.v2i2.2541.

[2] Symisius Lintang Ranataru and Nurvita Trianasari, "Analisis Sentimen Media Sosial Terhadap Aplikasi Perbankan Untuk Mengetahui Kepuasan Pengguna Aplikasi: Studi Kasus Pada Livin by Mandiri dan BCA Mobile," Al-Kharaj: Jurnal Ekonomi, Keuangan & Bisnis Syariah, vol. 6, no. 9, Sep. 2024, doi: 10.47467/alkharaj.v6i9.3805.

[3] M. Gamma, A. Hakim, and F. Irwiensyah, "Analisis Sentimen Terhadap Ulasan Pengguna Pada Aplikasi BCA Mobile Menggunakan Metode Naïve Bayes," Journal of Information System Research, vol. 5, no. 4, 2024, doi: 10.47065/josh.v5i4.5343.

[4] D. Munandar, M. Afdal, Z. Zarnelly, and R. Novita, “Analisis Sentimen Ulasan Pengguna Aplikasi Mobile Banking Menggunakan Algoritma K-Nearest Neighbor,” Jurnal Teknologi Sistem Informasi dan Aplikasi, vol. 7, no. 3, pp. 1309–1318, Jul. 2024, doi: 10.32493/jtsi.v7i3.41409.

[5] N. K. Putri, A. V. Vitianingsih, S. Kacung, A. L. Maukar, and V. Yasin, "Sentiment Analysis of Brand Ambassador Influence on Product Buyer Interest Using KNN and SVM," Indonesian Journal of Artificial Intelligence and Data Mining, vol. 7, no. 2, p. 327, Apr. 2024, doi: 10.24014/ijaidm.v7i2.29469.

[6] R. I. Putra Selian, A. V. Vitianingsih, S. Kacung, A. Lidya Maukar, and J. Febrian Rusdi, "Sentiment Analysis of Public Responses on Social Media to Satire Joke Using Naïve Bayes and KNN," sinkron, vol. 8, no. 3, pp. 1443–1451, Jul. 2024, doi: 10.33395/sinkron.v8i3.13721.

[7] J. Muliawan and E. Dazki, "Sentiment Analysis Of Indonesia's Capital City Relocation Using Three Algorithms: Naïve Bayes, Knn, And Random Forest," Jurnal Teknik Informatika (JUTIF), vol. 4, no. 5, pp. 1227–1236, 2023, doi: 10.52436/1.jutif.2023.4.5.347.

[8] S. L. Ranataru and N. Trianasari, "Analisis Sentimen Media Sosial Terhadap Aplikasi Perbankan Untuk Mengetahui Kepuasan Pengguna Aplikasi: Studi Kasus Pada Livin by Mandiri dan BCA Mobile," Al-Kharaj: Jurnal Ekonomi, Keuangan & Bisnis Syariah, vol. 6, no. 9, 2024, doi: 10.47467/alkharaj.v6i9.3805.

[9] S. Rabbani, D. Safitri, N. Rahmadhani, A. A. F. Sani, and M. K. Anam, “Perbandingan Evaluasi Kernel SVM untuk Klasifikasi Sentimen dalam Analisis Kenaikan Harga BBM,” MALCOM: Indonesian Journal of Machine Learning and Computer Science, vol. 3, no. 2, pp. 153–160, Oct. 2023, doi: 10.57152/malcom.v3i2.897.

[10] D. Oktavia and Y. R. Ramadahan, "Analisis Sentimen Terhadap Penerapan Sistem E-Tilang Pada Media Sosial Twitter Menggunakan Algoritma Support Vector Machine (SVM)," Media Online, vol. 4, no. 1, pp. 407–417, 2023, doi: 10.30865/klik.v4i1.1040.

[11] D. Nurmalasari, T. I. Hermanto, and I. M. Nugroho, “Perbandingan Algoritma SVM, KNN dan NBC Terhadap Analisis Sentimen Aplikasi Loan Service,” JURNAL MEDIA INFORMATIKA BUDIDARMA, vol. 7, no. 3, p. 1521, Jul. 2023, doi: 10.30865/mib.v7i3.6427.

[12] E. Damayanti, A. V. Vitianingsih, S. Kacung, H. Suhartoyo, and A. Lidya Maukar, "Sentiment Analysis of Alfagift Application User Reviews Using Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) Methods," Decode: Jurnal Pendidikan Teknologi Informasi, vol. 4, no. 2, pp. 509–521, Jun. 2024, doi: 10.51454/decode.v4i2.478.

[13] A. Casini, D. Chelazzi, and P. Baglioni, "Advanced methodologies for the cleaning of works of art," Aug. 01, 2023, Science Press. Doi: 10.1007/s11431-022-2348-7.

[14] S. Ramadhani, D. Azzahra, and T. Z, "Comparison of K-Means and K-Medoids Algorithms in Text Mining based on Davies Bouldin Index Testing for Classification of Student's Thesis," Digital Zone: Jurnal Teknologi Informasi dan Komunikasi, vol. 13, no. 1, pp. 24–33, May 2022, doi: 10.31849/digitalzone.v13i1.9292.
[15] R. Fatmasari, N. Purnomo, S. A. Putra, W. Gata, and N. K. Wardhani, "Pengujian Pelabelan Otomatis Dataset Kualitas Pembelajaran Daring Universitas Terbuka Di Forum Dan Youtube," JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika), vol. 9, no. 3, pp. 1714–1724, Sep. 2024, doi: 10.29100/jipi.v9i3.5231.
[16] C. Kumaresan and P. Thangaraju, "Sentiment Analysis in Multiple Languages: A Review of Current Approaches and Challenges," REST Journal on Data Analytics and Artificial Intelligence, vol. 2, no. 1, pp. 8–15, Mar. 2023, doi: 10.46632/jdaai/2/1/2.
[17] K. Kiazad, S. L. D. Restubog, P. W. Hom, A. Capezio, B. Holtom, and T. Lee, "STEMming the tide: New perspectives on careers and turnover," J Organ Behav, vol. 45, no. 3, pp. 335–343, Mar. 2024, doi: 10.1002/job 2780.
[18] Y. Asri, W. N. Suliyanti, D. Kuswardani, and M. Fajri, "Pelabelan Otomatis Lexicon Vader dan Klasifikasi Naive Bayes dalam menganalisis sentimen data ulasan PLN Mobile," PETIR, vol. 15, no. 2, pp. 264–275, Nov. 2022, doi: 10.33322/petir.v15i2.1733.
[19] D. Nurmalasari, T. I. Hermanto, and I. M. Nugroho, "Perbandingan Algoritma SVM, KNN dan NBC Terhadap Analisis Sentimen Aplikasi Loan Service," JURNAL MEDIA INFORMATIKA BUDIDARMA, vol. 7, no. 3, p. 1521, 2023, doi: 10.30865/mib.v7i3.6427.
[20] H. D. Abubakar and M. Umar, "Sentiment Classification: Review of Text Vectorization Methods: Bag of Words, Tf-Idf, Word2vec and Doc2vec," SLU Journal of Science and Technology, vol. 4, no. 1 & 2, pp. 27–33, Aug. 2022, doi: 10.56471/slujst.v4i.266.
[21] D. Nurmalasari, T. I. Hermanto, and I. M. Nugroho, "Perbandingan Algoritma SVM, KNN dan NBC Terhadap Analisis Sentimen Aplikasi Loan Service," JURNAL MEDIA INFORMATIKA BUDIDARMA, vol. 7, no. 3, p. 1521, Jul. 2023, doi: 10.30865/mib.v7i3.6427.
[22] I. Alpian Novansyah and T. Suprapti, "Analisis Sentimen Pengguna Pada Aplikasi Lingokids Menggunakan Metode K-Nearest Neighbour," 2023.
[23] M. J. Palepa, N. Pratiwi, and R. Q. Rohmansa, "Analisis Sentimen Masyarakat Tentang Pengaruh Politik Identitas Pada Pemilu 2024 Terhadap Toleransi Beragama Menggunakan Metode K - Nearest Neighbor," JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika), vol. 9, no. 1, pp. 389–401, Feb. 2024, doi: 10.29100/jipi.v9i1.4957.
[24] A. Witanti, B. Yogyakarta Jl Raya Wates-Jogjakarta, K. Sedayu, K. Bantul, and D. Istimewa Yogyakartalamat, "Analisis Sentimen Masyarakat Terhadap Vaksinasi Covid-19 Pada Media Sosial Twitter Menggunakan Algoritma Support Vector Machine (SVM)," Jurnal Sistem Informasi dan Informatika (Simika) P-ISSN, vol. 5, pp. 2622–6901, 2022.
[25] T. T. Thet, J. C. Na, and C. S. G. Khoo, "Aspect-based sentiment analysis of movie reviews on discussion boards," J Inf Sci, vol. 36, no. 6, pp. 823–848, Dec. 2010, doi: 10.1177/0165551510388123.
[26] D. Valero-Carreras, J. Alcaraz, and M. Landete, "Comparing two SVM models through different metrics based on the confusion matrix," Comput Oper Res, vol. 152, Apr. 2023, doi: 10.1016/j.cor.2022.106131.

BIBLIOGRAPHY OF AUTHORS

Yosefin Yuniati Zandroto is an active final semester student in the Department of Informatics at Dr.Soetomo University, Surabaya, Indonesia. The author is interested in data science.

Anik Vega Vitianingsih is currently a lecturer at the Informatics Department of Universitas Dr. Soetomo, Surabaya, Indonesia. Her research focuses on machine learning-based spatial analysis, particularly in the application and development of GIS, as well as in the broader field of natural language processing, with a specific focus on sentiment analysis.

Anastasia Lidya Maukar is currently a lecturer at President University in Indonesia, where she teaches courses on industrial management and information systems development. S.T., M.Sc., and M.MT. are the degrees that she also possesses. Both the University of Hertfordshire and the Institut Teknologi Sepuluh Nopember Surabaya (ITS) awarded their master's degrees in information systems development and industrial management, respectively. Her academic background includes both of these degrees. Information systems, databases, statistics, and production systems are all examples of topics that can have research applications.

Nina Kurnia Hikmawati is currently working as a lecturer at Universitas Komputer Indonesia (UNIKOM), where she teaches Information Systems. Her academic background is in the field of Management and Information Systems, which provides a comprehensive understanding of organizational management and the use of information technology to support decision-making and operational efficiency.

Rusdi Hamidan is a lecturer at Universitas Dr. Soetomo, Surabaya. He is particularly interested in Web and Mobile Development, especially in Kotlin for Mobile Device Programming and modern Web Front-End Development. He also enjoys exploring API integration, Object-Oriented Programming, and advanced software development concepts.