Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

Enhancing Sentiment Classification Performance on Tentang Anak Application Reviews Using Optimized Support Vector Machine

Riska Aryanti[1*], Eka Fitriani[2], Royadi[3], Dian Ardiansyah[4]
[1,2,3,4]Faculty of Engineering and Informatics, Universitas Bina Sarana Informatika, Indonesia
[1*]riska.rts@bsi.ac.id, [2]eka.ean@bsi.ac.id, [3]royadi.roo@bsi.ac.id, [4]dian.did@bsi.ac.id

Abstract: The increasing use of parenting and child development applications has generated a large volume of user reviews containing valuable insights regarding application quality, usability, and user satisfaction. One of the widely used applications in Indonesia is Tentang Anak: Kehamilan & Anak. However, manually analyzing these reviews is inefficient due to the large amount of unstructured textual data. Therefore, this study aims to enhance sentiment classification performance on user reviews of the Tentang Anak: Kehamilan & Anak application using an optimized Support Vector Machine (SVM) model. The dataset consisted of user reviews collected from application platforms, which were processed through several text preprocessing stages, including cleaning, normalization, tokenization, stopword removal, and stemming. Sentiment labeling was conducted using polarity scores to classify reviews into positive and negative sentiments. The proposed model was evaluated using different test size scenarios (0.1, 0.2, 0.3, and 0.4) and random state configurations to identify the optimal parameter setting. Experimental results demonstrate that the best performance was achieved at a test size of 0.1 with random state 0, obtaining an accuracy of 89.8%, precision of 91.7%, recall of 55.0%, and F1-score of 68.8%. The findings indicate that the optimized SVM model is effective in classifying sentiment in reviews of the Tentang Anak: Kehamilan & Anak application, particularly in achieving high precision and classification stability across multiple testing scenarios. Furthermore, the study highlights the importance of parameter optimization in improving sentiment analysis performance for user-generated textual data.
Keywords: Sentiment Analysis; Support Vector Machine; Hyperparameter Optimization; Tentang Anak Application; Text Mining; Machine Learning

1. INTRODUCING

The rapid advancement of digital technology has significantly transformed healthcare services, particularly through the emergence of mobile health (m-health) applications that provide users with easier access to healthcare information and monitoring systems [1]. In recent years, parenting and maternal-child healthcare applications have experienced substantial growth due to increasing public awareness regarding child development [2], pregnancy monitoring, nutrition management, and preventive healthcare practices. The widespread adoption of smartphones has accelerated the use of digital healthcare platforms, enabling parents to monitor their children's growth and development more

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

efficiently through mobile applications [3][4]. As the number of users continues to increase, these applications generate a large volume of user reviews containing valuable information related to service quality, usability, feature effectiveness, and overall user satisfaction [5]. User-generated reviews therefore represent an important source of information that can support application evaluation and continuous service improvement within the digital healthcare ecosystem [6], [7].

One of the rapidly growing parenting applications in Indonesia is Tentang Anak: Kehamilan & Anak, which was developed collaboratively by pediatricians, child psychologists, and trusted healthcare experts. The application has also become an official partner of the Indonesian Ministry of Health (Kemenkes), Ministry of Education (Kemendikbud), and the National Population and Family Planning Agency (BKKBN). The platform is specifically designed to assist parents throughout pregnancy and child development stages by providing integrated services such as child growth monitoring, developmental tracking, vaccination reminders, nutritional recommendations, parenting education, health screening, and consultation with healthcare experts. Due to its comprehensive features and increasing popularity, the application receives a substantial amount of user feedback in the form of online reviews [8]. These reviews reflect users' experiences, expectations, and satisfaction regarding the services provided by the application.

User reviews contain both positive and negative opinions that can provide meaningful insights into user satisfaction and application performance. Positive reviews generally indicate successful service delivery and user acceptance, whereas negative reviews often reveal technical issues, usability limitations, and unmet user expectations. However, manually analyzing large-scale textual reviews is highly inefficient and time-consuming due to the unstructured nature of textual data. Consequently, automated sentiment analysis techniques are required to identify sentiment tendencies and extract meaningful information from user-generated content. Sentiment analysis has become one of the most widely studied topics in Natural Language Processing and text mining because it enables the automatic classification of opinions, emotions, and attitudes expressed in textual information. In healthcare-related applications, sentiment analysis can support service evaluation, identify user concerns, and improve user-centered digital healthcare systems.

Various machine learning methods have been widely implemented for sentiment classification tasks, including K-Nearest Neighbors [9], Decision Tree, Random Forest, Logistic Regression, and Deep Learning approaches. Among these algorithms, Support Vector Machine (SVM) is recognized as one of the most effective methods for text classification because of its strong capability in handling high-dimensional and sparse textual data. SVM constructs an optimal separating hyperplane between sentiment classes, enabling robust classification performance even when dealing with complex textual representations [10], [11]. Previous studies have demonstrated that SVM achieves competitive performance in sentiment analysis tasks across multiple domains, including e-commerce [12], tourism [13], [14], [15], healthcare [16], and social media analytics [17]. Nevertheless, the effectiveness of SVM is highly dependent on parameter configuration, data distribution, and preprocessing quality. Improper parameter settings may reduce classification accuracy and limit the model's ability to generalize sentiment patterns effectively.

Although numerous studies have explored sentiment analysis using SVM, most previous research has focused primarily on general domains such as product reviews, social media discussions, and online commerce platforms. Limited studies specifically investigate sentiment classification in parenting and maternal-child healthcare applications, particularly within the Indonesian-language context. Furthermore, previous works often emphasize overall accuracy without comprehensively evaluating model robustness across multiple experimental configurations. The influence of varying test size distributions and

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

random state configurations on sentiment classification stability also remains underexplored. This limitation indicates the need for a more comprehensive evaluation framework capable of identifying the optimal parameter configuration for Indonesian-language parenting-health application reviews.

To address these limitations, this study proposes an optimized Support Vector Machine-based sentiment analysis framework for classifying user reviews of the Tentang Anak: Kehamilan & Anak application. The proposed framework incorporates several preprocessing stages, including cleaning, case folding, normalization, tokenization, stopword removal, and stemming, to improve textual consistency prior to classification. In addition, the study evaluates multiple experimental scenarios involving different test size distributions and random state configurations to determine the most effective parameter setting for sentiment classification performance. The novelty of this study lies in the comprehensive robustness evaluation and parameter optimization of SVM for Indonesian parenting-health application reviews. Unlike previous studies that rely on single experimental settings, this research systematically investigates the influence of multiple parameter configurations on classification stability using several evaluation metrics, including accuracy, precision, recall, and F1-score. The findings of this study are expected to provide both theoretical and practical contributions to sentiment analysis research and digital healthcare service evaluation by offering empirical insights into user perceptions and application performance within the parenting-health domain.

2. RESEARCH METHODOLOGY

The research process began with the data collection stage, which involved installing the Google Play Store scraping library to retrieve user review data from the Google Play Store platform. After the data acquisition process was completed, several preprocessing procedures were performed to transform the raw and unstructured textual data into a cleaner and more structured format suitable for further analysis. The preprocessing stage included data cleaning and preparation to improve textual consistency and reduce irrelevant information. Since the collected reviews initially did not contain sentiment labels, a labeling process was subsequently conducted using a lexicon-based approach to calculate the polarity score of each review. Through this approach, reviews were categorized into positive or negative sentiment classes based on the identified polarity values. Following the labeling stage, the dataset was divided into training and testing datasets to support the classification process. Furthermore, multiple experimental scenarios were conducted to evaluate the classification performance by identifying the optimal data splitting parameters capable of producing the highest accuracy while minimizing classification errors and improving model robustness. The overall framework of the proposed research methodology is presented in Figure 1.

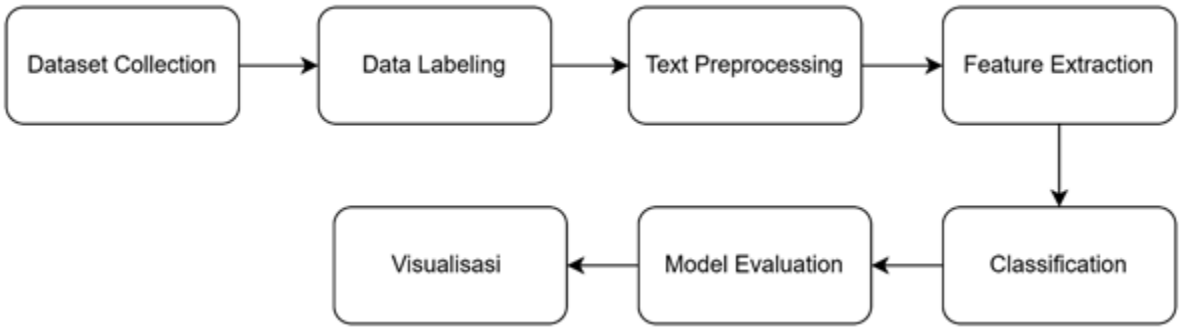

Figure 1. Research Method

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

2.1. Dataset Collection

The dataset used in this study consisted of user reviews collected from the Tentang Anak: Kehamilan & Anak app available on the Google Play Store platform. The reviews were gathered to analyze users' opinions, experiences, and satisfaction regarding the app's services and features. Data collection was conducted using a web scraping technique to automatically retrieve review information, including username, review content, rating score, and review date. table 1 shows dataset description.

Table 1. Dataset Description

#	Column	Data type
1	userName	object
2	score	int32
3	date	object
4	content	object

2.2. Data Labeling

The collected reviews were labeled into sentiment categories consisting of positive and negative sentiments. Sentiment labeling was performed using polarity score analysis based on the textual content of each review [13], [18]. Reviews containing positive opinions, appreciation, or satisfaction toward the application were labeled as positive sentiment, while reviews expressing complaints, dissatisfaction, or negative experiences were categorized as negative sentiment.

2.3. Text Preprocessing

Text preprocessing was conducted to improve textual data quality and reduce noise before feature extraction and classification processes[19], [20], [21]. Several preprocessing stages were applied sequentially as follows.

1. Cleaning

The cleaning stage aimed to remove unnecessary characters and irrelevant information from the reviews, including URLs, Emojis, Punctuation marks, Numbers, Special characters and Duplicate spaces [22].

2. Case Folding

Case folding transformed all characters into lowercase form to ensure consistency in textual representation [23].

3. Normalization

Normalization converted non-standard words, abbreviations, and informal expressions into standardized Indonesian words [23].

4. Tokenization

Tokenization separated sentences into individual words or tokens [24].

5. Stopword Removal

Stopword removal eliminated frequently occurring words that do not significantly contribute to sentiment classification, such as dan, yang, di, ke [25], [26].

6. Stemming

Stemming transformed words into their root forms to reduce word variation [27].

2.4. Feature Extraction

After preprocessing, textual data were transformed into numerical representations using the Term Frequency–Inverse Document Frequency (TF-IDF) method.

TF-IDF measures the importance of a word within a document relative to the entire dataset [28]. The method assigns higher weights to words that frequently appear in a specific document but rarely occur across other documents.

TF-IDF was used because it effectively represents textual data in high-dimensional feature spaces suitable for SVM classification.

2.5. Classification Model

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

This study employed Support Vector Machine (SVM) as the classification model for sentiment analysis.

SVM aims to identify the optimal hyperplane that maximizes the separation margin between positive and negative sentiment classes.

2.6. Model Evaluation

The evaluation process was conducted using several performance metrics, including accuracy, precision, recall, and F1-score. Accuracy represents the proportion of correctly classified instances produced by the model and reflects the overall classification performance. The accuracy value was obtained by comparing the number of correct predictions to the total number of predictions generated during the classification process.

2.7. Visualisasi

The final stage of the methodology involved result visualization and performance analysis. Word cloud visualization was used to identify dominant terms in positive and negative sentiment reviews of the Tentang Anak: Kehamilan & Anak application. In addition, graphical visualizations were generated to illustrate the changes in accuracy, precision, and recall values across different test size configurations, enabling evaluation of the performance stability of the Support Vector Machine (SVM) model.

3. RESULT AND DISCUSSIONS

3.1. Result

The first stage of this study involved collecting user review data from the Tentang Anak: Kehamilan & Anak application available on the Google Play Store platform. The data collection process was conducted using a scraping technique to retrieve textual reviews submitted by users. The collected reviews contained various opinions and experiences regarding the application features, including child growth monitoring, vaccination reminders, parenting education, and healthcare consultation services. Since the collected data were still unstructured and contained irrelevant textual components, further processing was required before conducting sentiment classification. Figure 2 shows dataset description

	userName	score	date	content
0	Setiawan Yuliantoro	5	2026-04-26	sangat membantu melihat track record pertumbuh...
1	Muhammad Bashar	5	2026-04-24	Sangat Bermanfaat Bisa jadi acuan untuk memant...
2	Rizki Meidina	5	2026-04-21	bagus banget jadi tau standar berat badan nya
3	Yuda Guntara	5	2026-04-20	mempermudah untuk mengetahui tumbang anakk
4	Candra Sutrisna	5	2026-04-13	mantap sangat membantu agar lebih mudah belaja...

Figure 2. Sample Dataset

After the dataset collection process, sentiment labeling was performed to categorize the reviews into positive and negative sentiment classes. The labeling stage utilized a lexicon-based approach to calculate the polarity score of each review. Reviews containing positive expressions, appreciation, and satisfaction toward the application were categorized as positive sentiment, whereas reviews expressing complaints, dissatisfaction, or negative experiences were classified as negative sentiment. This labeling process was essential for constructing the supervised learning model used in the classification stage. Figure 3 shows Distribution of positive and negative classes.

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

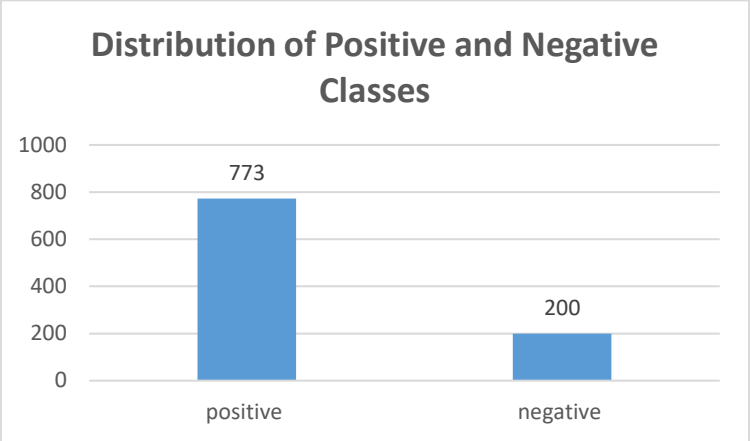

Figure 3. Distribution of Positive and Negative Classes

As shown in Figure 2, the dataset consists of 773 positive reviews and 200 negative reviews. The sentiment class distribution shows that positive sentiment dominates the dataset, indicating that the majority of users expressed satisfaction with the services and features provided by the app.

The collected reviews underwent several preprocessing stages to improve textual quality and reduce noise within the dataset. The preprocessing process included cleaning, case folding, normalization, tokenization, stopword removal, and stemming. The cleaning stage removed unnecessary characters such as punctuation marks, emojis, URLs, numbers, and special symbols. Case folding transformed all characters into lowercase form to maintain textual consistency. Normalization converted informal Indonesian words into standardized forms, while tokenization separated sentences into individual tokens. Furthermore, stopword removal eliminated commonly used words that did not contribute significantly to sentiment classification, and stemming transformed words into their root forms to reduce lexical variation. Table 2 shows sample results of text preprocessing, polarity scoring, and sentiment labeling. These preprocessing stages substantially improved textual consistency and prepared the data for feature extraction

Table 2. Examples of Text Preprocessing and Sentiment Labeling Results

Before Text Preprocessing	After Text Preprocessing	polarity score	Label
tolong revisi vaksinnya karna tidak sesuai sama di buku kia huhuhu... polio 1 sama bcg pas 1 bulan baru dikasih, gak ada polio 0 jadi, bingung isinya karna beda.	['tolong', 'revisi', 'vaksin', 'sesuai', 'buku', 'huhuhu', 'polio', 'kasih', 'polio', 'bingung', 'isi', 'beda']	-2	Negative
apl nya sangat2 bagus buanget dan bisa bantu buat selalu pantau pertumbuhan sikecil 🤗 sangat recommend dan isinya komplit bgt,ada bintang 100 tak kasih bintang 100 dah 🤗 🤗	['bagus', 'buanget', 'bantu', 'pantau', 'tumbuh', 'sikecil', 'rekomendasi', 'isi', 'komplet', 'banget', 'bintang', 'kasih', 'bintang']	1	Positive
setelah di update tampilan menjadi bagus, info lengkap, fitur banyak yang baru. Sayangnya di saya sering ngelag baru aja di buka.	['baru', 'tampil', 'bagus', 'informasi', 'lengkap', 'fitur', 'sayang', 'lambat', 'buka']	-5	Negative
Sangat Bermanfaat Bisa jadi acuan untuk memantau perkembangan Janin dan bayi setelah lahir	['manfaat', 'acu', 'pantau', 'kembang', 'janin', 'bayi', 'lahir']	6	Positive

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

Table 2 presents examples of the text preprocessing and sentiment labeling results obtained from user reviews of the Tentang Anak: Kehamilan & Anak application. The table illustrates the transformation process from raw textual reviews into structured textual representations suitable for sentiment analysis. The preprocessing stage involved several procedures, including cleaning, normalization, tokenization, stopword removal, and stemming, resulting in a more consistent and simplified textual format.

The table also displays the polarity score generated using the lexicon-based approach to determine sentiment orientation. Reviews with positive polarity values were categorized as positive sentiment, while reviews with negative polarity values were classified as negative sentiment. For example, reviews containing words such as "bagus," "recommend," and "bantu" produced positive polarity scores and were labeled as positive sentiment. In contrast, reviews containing terms such as "revisi," "bingung," and "sayang" generated negative polarity scores and were categorized as negative sentiment. These results demonstrate that the preprocessing and labeling stages successfully transformed unstructured user reviews into structured sentiment data suitable for the classification process using the Support Vector Machine (SVM) model.

Following the preprocessing stage, the textual data were transformed into numerical representations using Term Frequency–Inverse Document Frequency (TF-IDF). This feature extraction technique effectively represented the importance of words within the dataset and generated high-dimensional feature vectors suitable for sentiment classification. The classification process was subsequently performed using the Support Vector Machine (SVM) algorithm. To evaluate model robustness and identify the optimal parameter configuration, multiple experimental scenarios were conducted using variations in test size and random state values. The test size configurations included 0.1, 0.2, 0.3, and 0.4, while several random state values were implemented to analyze classification consistency under different data distributions.

Table 3. Evaluation Results of Support Vector Machine (SVM) Algorithm

#	Test Size	Random State	Confusion Matrix	Accuracy	Recall	Precision	F1 Score
0	0.1	0	[[77, 1], [9, 11]]	0.898	0.550	0.917	0.688
1		5	[[79, 1], [10, 8]]	0.888	0.444	0.889	0.593
2		10	[[73, 2], [14, 9]]	0.837	0.391	0.818	0.529
3		15	[[80, 1], [11, 6]]	0.878	0.353	0.857	0.500
4		20	[[76, 0], [12, 10]]	0.878	0.455	1.000	0.625
5		25	[[69, 0], [16, 13]]	0.837	0.448	1.000	0.619
6	0.2	0	[[158, 3], [17, 17]]	0.897	0.500	0.850	0.630
7		5	[[151, 2], [22, 20]]	0.877	0.476	0.909	0.625
8		10	[[150, 4], [23, 18]]	0.862	0.439	0.818	0.571
9		15	[[159, 5], [23, 8]]	0.856	0.258	0.615	0.364
10		20	[[152, 0], [25, 18]]	0.872	0.419	1.000	0.590
11		25	[[140, 5], [26, 24]]	0.841	0.480	0.828	0.608
12	0.3	0	[[232, 6], [25, 29]]	0.894	0.537	0.829	0.652
13		5	[[228, 2], [41, 21]]	0.853	0.339	0.913	0.494
14		10	[[221, 7], [42, 22]]	0.832	0.344	0.759	0.473
15		15	[[237, 4], [34, 17]]	0.870	0.333	0.810	0.472
16		20	[[224, 1], [39, 28]]	0.863	0.418	0.966	0.583

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

#	Test Size	Random State	Confusion Matrix	Accuracy	Recall	Precision	F1 Score
17	0.4	25	[[217, 4], [41, 30]]	0.846	0.423	0.882	0.571
18		0	[[301, 6], [59, 24]]	0.833	0.289	0.800	0.425
19		5	[[305, 2], [55, 28]]	0.854	0.337	0.933	0.496
20		10	[[299, 11], [54, 26]]	0.833	0.325	0.703	0.444
21		15	[[312, 8], [49, 21]]	0.854	0.300	0.724	0.424
22		20	[[292, 4], [63, 31]]	0.828	0.330	0.886	0.481
23		25	[[298, 1], [60, 31]]	0.844	0.341	0.969	0.504

The confusion matrix analysis indicates that the proposed SVM model successfully minimized false positive predictions, as reflected by the high precision value achieved during classification. Most negative sentiment reviews were correctly identified without being misclassified as positive sentiment. However, the model still experienced limitations in detecting all positive sentiment instances optimally, which is reflected in the relatively moderate recall value. This limitation may have been influenced by class imbalance, short-text review characteristics, and ambiguous contextual expressions commonly found in Indonesian-language user reviews. The lower recall performance suggests that the model tended to prioritize classification certainty over sensitivity toward minority sentiment classes. Since the dataset was dominated by positive reviews, the SVM model learned dominant sentiment patterns more effectively than minority patterns. Consequently, some positive sentiment instances containing implicit or mixed emotional expressions were incorrectly classified, reducing the overall recall performance.

As presented in Table 3, the experimental results demonstrated that parameter configuration significantly influenced classification performance. The best performance was achieved using a test size of 0.1 and random state 0, resulting in an accuracy of 89.8%, precision of 91.7%, recall of 55.0%, and F1-score of 68.8%. These findings indicate that the optimized Support Vector Machine (SVM) model was highly effective in minimizing false positive predictions while maintaining stable classification performance across multiple experimental scenarios. The high precision value suggests that the model successfully identified positive sentiment reviews with relatively low prediction errors. However, the recall value remained relatively moderate, indicating that the model still encountered difficulties in correctly identifying all positive sentiment instances. This limitation may have been influenced by the imbalance between positive and negative sentiment classes as well as the presence of short-text reviews containing ambiguous contextual expressions.

Figure 4. Wordcloud Tentang Anak Application

Figure 4 presents the word cloud visualization generated from user reviews of the Tentang Anak: Kehamilan & Anak application. The visualization illustrates the most

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

frequently occurring words within the review dataset, where larger word sizes indicate higher frequencies of occurrence. Based on the word cloud, dominant terms such as "anak," "tumbuh," "kembang," "terima kasih," "manfaat," "mudah," "fitur," and "informasi" appeared prominently in the dataset. The frequent occurrence of these words indicates that users generally perceived the application positively, particularly regarding its usefulness in supporting child growth monitoring, parenting assistance, and access to healthcare-related information.

The dominance of words such as "tumbuh kembang," "pantau," and "anak" suggests that the application successfully fulfills its primary function as a parenting and child development monitoring platform. Furthermore, terms such as "mudah," "lengkap," and "manfaat" indicate that users appreciated the usability, completeness of features, and practical benefits provided by the application. The appearance of words related to healthcare services, including "dokter," "resep," "gizi," and "konsultasi," also demonstrates that users actively utilized healthcare-oriented features available within the platform.

Overall, the word cloud visualization reveals that most user reviews contained positive expressions and satisfaction-related terms, supporting the sentiment distribution results in which positive reviews dominated the dataset. These findings indicate that the Tentang Anak: Kehamilan & Anak application was generally well received by users and effectively assisted parents in monitoring child development and accessing parenting-related healthcare services.

3.2. Discussions

The experimental findings demonstrate that parameter configuration plays a significant role in determining sentiment classification performance. The variation of test size and random state values directly influenced the distribution of training and testing data, affecting the model's ability to generalize sentiment patterns.

The results also confirm that Support Vector Machine remains highly effective for Indonesian-language text classification tasks because of its capability to handle sparse and high-dimensional textual representations generated by TF-IDF feature extraction. The preprocessing stages, particularly stemming and normalization, substantially contributed to improving feature consistency and reducing lexical variations commonly found in Indonesian user reviews.

Compared to previous sentiment analysis studies focusing on general domains such as e-commerce and social media, this study specifically contributes to parenting-health application analytics. The findings provide empirical evidence that optimized SVM models can effectively classify sentiments in healthcare-related application reviews while maintaining stable precision across multiple experimental scenarios.

However, several limitations were identified in this study. The relatively lower recall values indicate that the model still encountered difficulties in correctly identifying all positive sentiment instances.

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

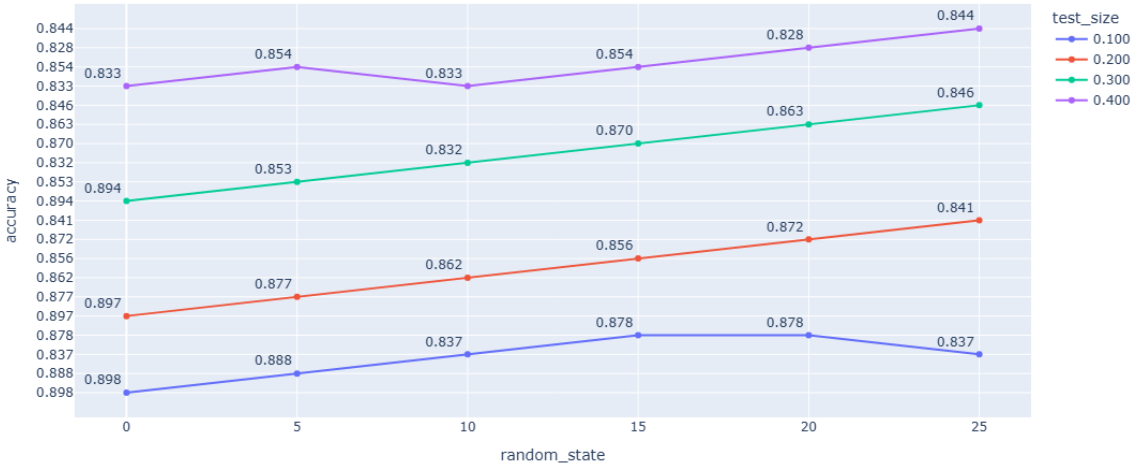

Figure 5. Accuracy Performance Across Test Size Configurations

Figure 5 illustrates the accuracy performance of the Support Vector Machine (SVM) model across different test size configurations. Based on the visualization, the highest accuracy was achieved at a test size of 0.1, indicating that the model performed more effectively when a larger proportion of the dataset was allocated for training. As the test size increased, the accuracy values tended to decrease gradually. This finding suggests that reducing the amount of training data limited the model's ability to learn sentiment patterns comprehensively. Overall, the graph demonstrates that the distribution of training and testing data significantly influenced the classification performance of the proposed model.

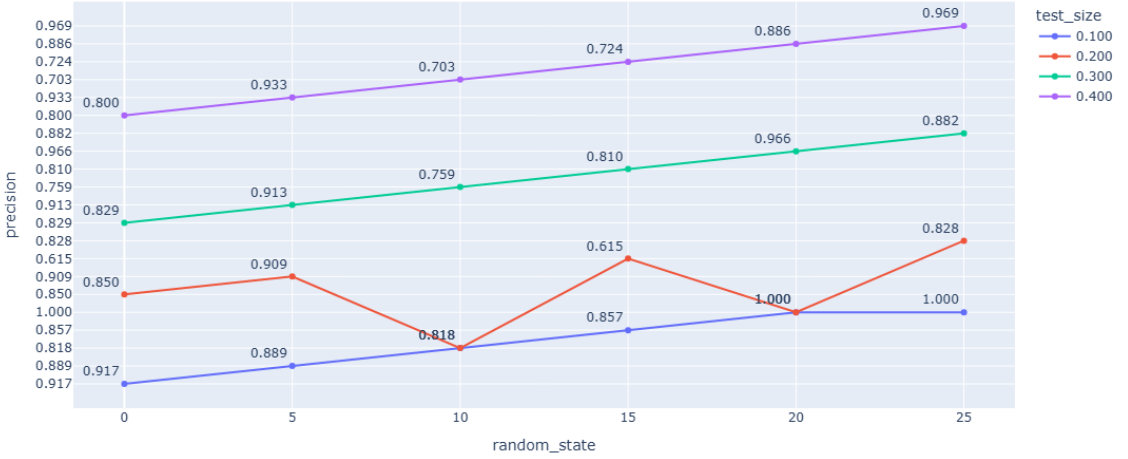

Figure 6. Precision Performance Across Test Size Configurations

Figure 6 presents the precision values obtained from different test size scenarios. The visualization shows that the SVM model consistently achieved relatively high precision values across multiple configurations, with the best precision obtained at a test size of 0.1. The high precision performance indicates that the model was highly effective in minimizing false positive predictions when classifying positive sentiment reviews. Although slight fluctuations occurred as the test size increased, the precision values remained relatively stable, demonstrating that the model maintained strong discriminative capability despite variations in data partitioning.

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

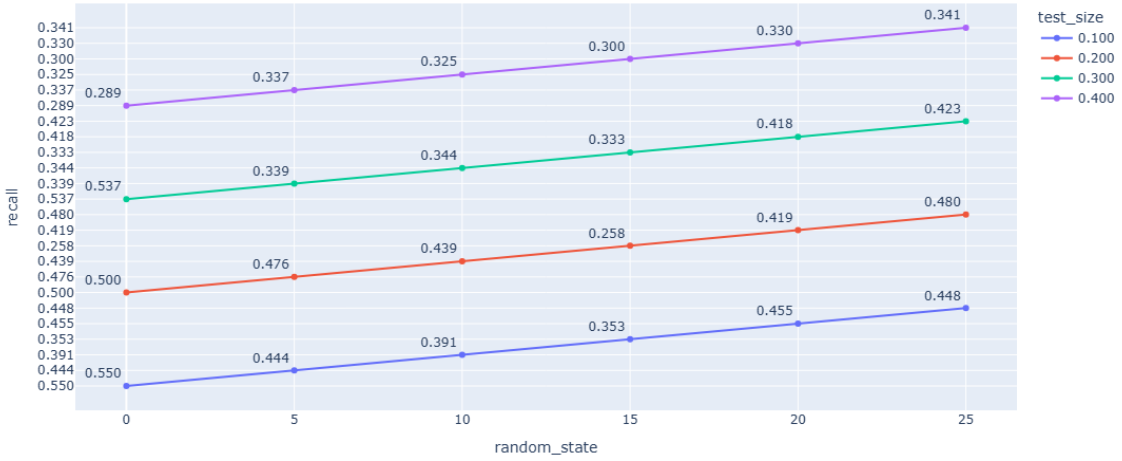

Figure 7. Recall Performance Across Test Size Configurations

Figure 7 illustrates the recall performance of the Support Vector Machine (SVM) model under different test size configurations. Unlike accuracy and precision, the recall values showed more noticeable fluctuations across experimental scenarios. The highest recall value was obtained at a test size of 0.1, while larger test size configurations generally resulted in lower recall performance. This finding indicates that the model experienced greater difficulty in correctly identifying all positive sentiment instances when the amount of training data decreased. The relatively moderate recall values were likely influenced by the imbalance between positive and negative sentiment classes as well as the presence of short-text reviews containing ambiguous contextual expressions.

4. CONCLUSION

This study proposed an optimized Support Vector Machine (SVM)-based sentiment analysis framework for classifying user reviews of the Tentang Anak: Kehamilan & Anak application. The research was conducted to analyze user sentiments toward parenting-health application services and to identify the optimal parameter configuration capable of improving sentiment classification performance. The proposed framework integrated several preprocessing stages, including cleaning, case folding, normalization, tokenization, stopword removal, and stemming, followed by Term Frequency–Inverse Document Frequency (TF-IDF) feature extraction and SVM classification.

The experimental results demonstrated that parameter configuration significantly influenced classification performance and model robustness. Among the evaluated scenarios, the best performance was achieved using a test size of 0.1 and random state 0, producing an accuracy of 89.8%, precision of 91.7%, recall of 55.0%, and F1-score of 68.8%. These findings indicate that the optimized SVM model was highly effective in minimizing false positive predictions and maintaining stable sentiment classification performance across multiple experimental scenarios. In addition, the preprocessing techniques substantially improved textual consistency and reduced lexical variations commonly found in Indonesian-language user reviews, contributing to more effective feature representation and classification results.

The findings of this study provide several important benefits and practical implications. From an academic perspective, this research contributes to the relatively underexplored area of sentiment analysis for parenting and maternal-child healthcare applications in the Indonesian-language context. The study also demonstrates the importance of evaluating multiple parameter configurations to improve classification robustness in textual sentiment analysis tasks. From a practical perspective, the proposed framework can assist developers of digital healthcare applications in understanding user perceptions, identifying service limitations, and improving application quality based on sentiment-driven evaluation. The

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

results may also support decision-making processes for enhancing user experience and healthcare-related digital services.

Despite achieving promising performance, several limitations remain in this study. First, the dataset was limited to user reviews collected from a single application platform, which may reduce the generalizability of the findings. Second, the sentiment classification process focused only on binary sentiment categories, namely positive and negative sentiments, without considering neutral or mixed emotional expressions. Third, the relatively moderate recall values indicate that the SVM model still experienced difficulty in correctly identifying all positive sentiment instances, particularly due to class imbalance, short-text characteristics, and contextual ambiguity in informal Indonesian language usage.

Therefore, future research is recommended to utilize larger and more diverse datasets collected from multiple digital platforms to improve model generalization and robustness. Further studies are also encouraged to implement data balancing techniques such as SMOTE to address sentiment imbalance issues and improve recall performance. In addition, comparisons between SVM and advanced deep learning approaches, including Long Short-Term Memory (LSTM), Bidirectional LSTM, and transformer-based models such as BERT or IndoBERT, are recommended to enhance contextual understanding and sentiment classification accuracy. Future work may also explore aspect-based sentiment analysis to provide more detailed insights into specific application features that influence user satisfaction and dissatisfaction.

5. REFERENCES

[1] N. Naik *et al.*, "Transforming healthcare through a digital revolution: A review of digital healthcare technologies and solutions," *Front. Digit. Health*, vol. 4, no. 919985, Aug. 2022, doi: 10.3389/fdgth.2022.919985.

[2] S. Till *et al.*, "Digital Health Technologies for Maternal and Child Health in Africa and Other Low- and Middle-Income Countries: Cross-disciplinary Scoping Review with Stakeholder Consultation," *J. Med. Internet Res.*, vol. 6, no. 6, Jun. 2023, doi: 10.2196/42161.

[3] P. Kitsao-Wekulo, N. Kipkoech Langat, M. Nampijja, E. Mwaniki, K. Okelo, and E. Kimani-Murage, "Development and feasibility testing of a mobile phone application to track children's developmental progression," *PLoS One*, vol. 16, no. 7, Jul. 2021, doi: 10.1371/journal.pone.0254621.

[4] T. C. Kustiawan, S. R. Nadhiroh, R. Ramli, and C. Butryee, "Use of mobile app to monitoring growth outcome of children: A systematic literature review," *Digit. Health*, vol. 8, Jan. 2022, doi: 10.1177/20552076221138641.

[5] R. Sevin and W. Humayrah, "Effect of Using the 'Tentang Anak' Application on Mothers' Knowledge, Attitudes, and Behavior in Monitoring the Nutritional Status of Under-two Children," *Aamerta Nutrition*, vol. 8, no. 2, pp. 180–189, Jun. 2024, doi: 10.20473/amnt.v8i2.2024.180- 189.

[6] Shahmirul Hafizullah Imanuddin, Kusworo Adi, and Rahmat Gernowo, "Sentiment Analysis on Satusehat Application Using Support Vector Machine Method," *Journal of Electronics, Electromedical Engineering, and Medical Informatics*, vol. 5, no. 3, pp. 143–149, Jul. 2023, doi: 10.35882/jeemi.v5i3.304.

[7] R. Guido, S. Ferrisi, D. Lofaro, and D. Conforti, "An Overview on the Advancements of Support Vector Machine Models in Healthcare Applications: A Review," *Information*, vol. 15, no. 4, p. 235, Apr. 2024, doi: 10.3390/info15040235.

[8] S. Bellary, P. Kumar Bala, and S. Chakraborty, "Utilizing online reviews for analyzing digital healthcare consultation services: Examining perspectives of both healthcare customers and healthcare professionals," *Int. J. Med. Inform.*, vol. 191, p. 105587, Nov. 2024, doi: 10.1016/j.ijmedinf.2024.105587.

Riska Aryanti: *Corresponding Author

[9] A. W. Sari, T. I. Hermanto, and M. Defriani, "Sentiment Analysis Of Tourist Reviews Using K-Nearest Neighbors Algorithm And Support Vector Machine," *Sinkron*, vol. 8, no. 3, pp. 1366–1378, Jul. 2023, doi: 10.33395/sinkron.v8i3.12447.
[10] D. Dan and T. Reutterer, "Text Classification, LDA, KNN, SVM, Neural Networks, and FastText," Springer, 2026, pp. 169–208. doi: 10.1007/978-3-032-08086-8_6.
[11] H. Allam, L. Makubvure, B. Gyamfi, K. N. Graham, and K. Akinwolere, "Text Classification: How Machine Learning Is Revolutionizing Text Categorization," *Information*, vol. 16, no. 2, p. 130, Feb. 2025, doi: 10.3390/info16020130.
[12] J. Iqbal *et al.*, "Sentiment Analysis Classification of E-commerce User Reviews Using Natural Language Processing (NLP) and Support Vector Machine (SVM) Methods," *Bulletin of Information Technology (BIT)*, vol. 6, no. 2, pp. 196–205, 2025, doi: 10.47065/bit.v5i2.2018.
[13] N. W. S. Saraswati, I. Ketut Gede Darma Putra, M. Sudarma, and I. Made Sukarsa, "Enhance sentiment analysis in big data tourism using hybrid lexicon and active learning support vector machine," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 5, pp. 3663–3674, Oct. 2024, doi: 10.11591/eei.v13i5.7807.
[14] Doni Abdul Fatah, Eka Mala Sari Rochman, Fajrul Ihsan Kamil, and Ahmad Su'ud, "Sentiment Analysis of Madura Tourism Opinion Using Support Vector Machine (SVM)," *Technium: Romanian Journal of Applied Sciences and Technology*, vol. 16, pp. 243–249, Oct. 2023, doi: 10.47577/technium.v16i.9988.
[15] M. P. Sharma, U. Meena, and G. K. Sharma, "Intelligent Data Analysis using Optimized Support Vector Machine Based Data Mining Approach for Tourism Industry," *ACM Trans. Knowl. Discov. Data*, vol. 16, no. 5, pp. 1–20, Oct. 2022, doi: 10.1145/3494566.
[16] S. Gohil, S. Vuik, and A. Darzi, "Sentiment Analysis of Health Care Tweets: Review of the Methods Used," *JMIR Public Health Surveill.*, vol. 4, no. 2, p. e43, Apr. 2018, doi: 10.2196/publichealth.5789.
[17] K.-X. Han, W. Chien, C.-C. Chiu, and Y.-T. Cheng, "Application of Support Vector Machine (SVM) in the Sentiment Analysis of Twitter DataSet," *Applied Sciences*, vol. 10, no. 3, p. 1125, Feb. 2020, doi: 10.3390/app10031125.
[18] R. Aryanti, E. Fitriani, R. Royadi, D. Ardiansyah, and A. Saepudin, "Sentiment Analysis of E-Grocery Application Reviews Using Lexicon-Based and Support Vector Machine," *Jurnal Riset Informatika*, vol. 6, no. 3, pp. 149–158, Jun. 2024, doi: 10.34288/jri.v6i3.301.
[19] U. Naseem, I. Razzak, and P. W. Eklund, "A survey of pre-processing techniques to improve short-text quality: a case study on hate speech detection on twitter," *Multimed. Tools Appl.*, vol. 80, no. 28–29, pp. 35239–35266, Nov. 2021, doi: 10.1007/s11042-020-10082-6.
[20] A. K. Uysal and S. Gunal, "The impact of preprocessing on text classification," *Inf. Process. Manag.*, vol. 50, no. 1, pp. 104–112, Jan. 2014, doi: 10.1016/j.ipm.2013.08.006.
[21] D. Ardiansyah, R. Aryanti, E. Fitriani, and R. Royadi, "Analisis Sentimen Pengguna GoPay pada Layanan Keuangan Digital dengan Perbandingan Naïve Bayes dan SVM," *Profitabilitas*, vol. 5, no. 2, pp. 83–89, 2025, [Online]. Available: https://jurnal.bsi.ac.id/index.php/profitabilitas
[22] M. Omar, A. Salah, and M. Mahdy, "Sentiment Analysis of Social Network Contents using Machine Learning Algorithms: A Review," 2025. [Online]. Available: https://www.ijci.zu.edu.eg
[23] A. Ramdhani, R. Aryanti, and S. Agustiani, "Optimasi Model Machine Learning Menggunakan Teknik SMOTE pada Analisis Sentimen Pengguna RedBus," *Journal of Artificial Intelligence and Technology Information*, vol. 4, no. 1, 2026, doi: 10.58602/jaiti.v4i1.182.

Riska Aryanti: *Corresponding Author

Journal of Artificial Intelligence and Technology Information
Website : https://ejournal.techcart-press.com/index.php/jaiti
E-ISSN 2985-6396
P-ISSN 2985-5306
Volume 4, Number 2, June 2026
https://doi.org/10.58602/jaiti.v4i2.271
Page 245-258

[24] V. K, P. Samuel, B. V. Krishna, and M. J, "Exploration of sentiment analysis in twitter propaganda: a deep dive," *Multimed. Tools Appl.*, vol. 83, no. 15, pp. 44729–44751, 2024, doi: 10.1007/s11042-023-17383-6.

[25] D. Toresa, S. Rico Francsisco Sitorus, I. Muzdalifah, F. Wiza, and R. Syelly, "Analisis Sentimen Terhadap Ulasan Penggunaan Dompet Digital Dana Mengunakan Metode Klasifikasi Support Vector Machine," *Technologica*, vol. 3, no. 2, pp. 64–74, Jul. 2024, doi: 10.55043/technologica.v3i2.163.

[26] D. W. Setyo Aji, A. Rohmani, and M. T. Sulistyono, "Sentiment Analysis Of The PPATK Bank Account Blocking Policy On Social Media X Using Tf-Idf And Smote With A Comparison Of Support Vector Machine And Decision Tree," *Rabit : Jurnal Teknologi dan Sistem Informasi Univrab*, vol. 11, no. 1, pp. 246–260, Jan. 2026, doi: 10.36341/rabit.v11i1.6877.

[27] M. Daffa, A. Fahreza, A. Luthfiarta, M. Rafid, M. Indrawan, and A. Nugraha, "Analisis Sentimen: Pengaruh Jam Kerja Terhadap Kesehatan Mental Generasi Z," *Journal of Applied Computer Science and Technology (JACOST)*, vol. 5, no. 1, pp. 16–25, 2024, doi: 10.52158/jacost.715.

[28] M. M. Danyal, S. S. Khan, M. Khan, S. Ullah, M. B. Ghaffar, and W. Khan, "Sentiment analysis of movie reviews based on NB approaches using TF–IDF and count vectorizer," *Soc. Netw. Anal. Min.*, vol. 14, no. 1, p. 87, Apr. 2024, doi: 10.1007/s13278-024-01250-9.

Riska Aryanti: *Corresponding Author