

Sentiment Analysis of User Reviews of the iPusnas Application on the Google Play Store: Insights into User Experience and Public Perception

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Abstract

Background: Digital library applications have expanded access to reading materials, making user experience an important dimension of service evaluation. iPusnas, developed by the National Library of Indonesia, has attracted substantial user engagement, reflected in the large number of reviews on the Google Play Store. These reviews provide valuable insights into public perception yet require systematic analysis to inform service improvement.

Objective: This study aims to examine user sentiment and emotional tendencies toward the iPusnas application based on Google Play Store reviews, with the goal of identifying key aspects of user experience that require attention.

Methods: This study applies a sentiment analysis approach to 500 user reviews collected through data scraping between 2024 and May 2025. The analysis involves text preprocessing, sentiment classification, and emotion detection using the SentiArt lexicon-based method, which enables the identification of affective dimensions in textual data. Model performance is evaluated using precision and recall metrics, and results are further explored through word frequency and topic patterns.

Results: The findings show that positive sentiment is primarily associated with expressions of satisfaction and enjoyment, while negative sentiment reflects frustration related to technical issues and service limitations. The classification model demonstrates relatively high precision for both positive (84.4%) and negative (94.7%) categories, but lower recall, indicating limitations in capturing diverse expressions of sentiment in Indonesian-language reviews. Thematic patterns highlight recurring concerns such as application stability, access to collections, and user interface experience.

Conclusion: User reviews of iPusnas reveal a combination of positive engagement and persistent technical concerns. The results suggest that sentiment analysis can support service evaluation but also highlight methodological challenges in accurately capturing nuanced expressions in Indonesian. Strengthening system performance and responsiveness to user feedback remains essential to enhancing the role of iPusnas in supporting digital literacy.

Keywords: *iPusnas, sentiment analysis; orange; user reviews; digital library application*

INTRODUCTION

The advancement of information technology has made it easier for people to access various information sources, including reading materials. If previously people had to visit a library to obtain reading materials, today they can access them directly through smartphones. One digital reading innovation developed in Indonesia is iPusnas, an application providing digital library services developed by the National Library of the Republic of Indonesia. Sulistyanto et al. in Ridha & Kusasi (2024) explain that iPusnas is a digital library developed by the National

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Library to facilitate public access to reading materials through electronic devices without having to purchase printed books or visit a physical library.

The adoption of this digital reading application is notably high, as its user base continues to grow. According to Kapusdatin (2025), as of December 2023, the number of iPusnas users reached 51,931. On Google Play Store, the application has been downloaded more than one million times and has received 34,100 reviews. The large number of users, downloads, and the positive impact on reading access means that different users will inevitably have varied experiences. These varied experiences translate into responses ranging from appreciation to complaints, expressed through various platforms including user reviews on Google Play Store.

To understand the extent of user experiences with iPusnas, a study aimed at mapping user perceptions is needed. One applicable approach is sentiment analysis, which involves text processing to identify opinions, emotions, and user assessments of an application or platform. In this regard, several previous studies have examined iPusnas application reviews using programming-based sentiment analysis, such as the work of Septiani & Budi (2022) using the CRISP-DM methodology with TF-IDF unigram (FI) feature combinations and SVM algorithm, yielding precision values as low as 55%, recall 42%, and F1-score 32%.

Subsequently, Naufal Zuhdi & Prasetyo (2025) employed the Naive Bayes algorithm and found that the reviews showed a high satisfaction rate of 75.1%. Based on the Naive Bayes algorithm, the accuracy rate was 58% with precision 60%, recall 81%, and F1-score 75%. Finally, Lestari et al. (2022) used Support Vector Machine (SVM) and found that the classification achieved an accuracy rate of 94.24%, with precision 92.38%, recall 83.86%, and F1-score 87.82%. Additionally, 75.1% of the review data were positive sentiment and 24.9% were negative.

Although these three studies make important contributions to understanding user views on iPusnas, certain limitations remain unaddressed. First, all three studies used programming-based approaches that tend to require specific technical skills. Second, they focused on sentiment polarity classification and performance evaluation without exploring the emotional dimensions underlying the reviews. Therefore, this study seeks to fill this gap by utilizing a visual platform, Orange, as an alternative for analyzing user reviews that not only provides insight into user perceptions but also offers a more practical and accessible approach.

Based on this background, the researcher is interested in conducting a study on Sentiment Analysis of iPusnas Application User Reviews on Google Play Store Using Orange. The research question is: how is the sentiment analysis of the iPusnas application based on Google Play Store user reviews using Orange?

LITERATURE REVIEW

Sentiment and Emotion in User-Generated Content

User-generated content, particularly in the form of online reviews, has become an important source for understanding public perception of digital services. Reviews reflect users'

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experiences, evaluations, and expectations, often expressed in unstructured textual form. To systematically interpret such data, sentiment analysis has been widely used as an approach to identify opinions, sentiments, and emotions embedded in text.

Sentiment analysis is generally defined as the computational study of opinions or emotions expressed in textual data. Nurian and Nurina Sari (2023) describe it as an effort to understand the sentiment contained in a piece of writing, while Sindhu et al. (2023) emphasize its role in identifying and classifying attitudes or emotions within text. Its primary purpose is to determine whether a text expresses positive, negative, or neutral sentiment toward a particular topic (Nhlabano & Lutu, 2018). In this sense, sentiment analysis provides a structured way to interpret user evaluations of products, services, or applications.

However, focusing solely on sentiment polarity may oversimplify user perception. Beyond positive or negative classifications, user reviews often contain emotional nuances such as satisfaction, frustration, or disappointment. These emotional dimensions are essential for understanding user experience more comprehensively, as they reveal not only what users think but also how they feel about a service.

Approaches to Sentiment Analysis

In analysing textual data, several methodological approaches have been developed. Broadly, sentiment analysis can be categorized into machine learning approaches and lexicon-based approaches. Machine learning methods, such as Support Vector Machines (SVM) and Multinomial Naïve Bayes, rely on training data to classify sentiment and are widely used for their predictive capabilities. Previous studies have demonstrated their application in various contexts, including digital service evaluation.

On the other hand, lexicon-based approaches utilize predefined word lists or dictionaries to determine sentiment orientation. These methods are often combined with preprocessing techniques such as cleaning, normalization, and transformation to improve data quality and analytical accuracy. Feature extraction techniques, including Term Frequency–Inverse Document Frequency (TF-IDF), are also commonly applied to enhance text representation (Ferdous et al., 2025; Khan, 2016; Nhlabano & Lutu, 2018; Yadav et al., 2023).

Compared to machine learning approaches, lexicon-based methods offer greater transparency and accessibility, particularly in contexts where annotated datasets are limited. Furthermore, they enable the exploration of affective or emotional dimensions in text, which can provide deeper insight into user experience beyond simple polarity classification.

Sentiment Analysis in the Context of iPusnas

As a digital library application developed by the National Library of Indonesia, iPusnas represents an important platform for expanding access to reading materials. The application allows users to access and borrow digital collections through electronic devices, thereby supporting the transformation of library services in the digital era (Prastiwi & Jumino, 2018; Herawan et al., 2023). With a growing number of collections and users, iPusnas has generated a substantial volume of user feedback, particularly through online reviews.

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Previous studies have examined iPusnas user reviews using sentiment analysis techniques. Lestari et al. (2022), Naufal Zuhdi and Prasetyo (2025), and Septiani and Budi (2022) primarily applied machine learning approaches such as SVM and Naïve Bayes to classify sentiment and evaluate model performance. These studies provide useful insights into the distribution of user sentiment and the effectiveness of different algorithms.

However, several limitations can be identified. First, prior research tends to emphasize model accuracy and performance metrics, with less attention given to interpreting the results in relation to user experience. Second, most studies focus on sentiment polarity without examining the emotional dimensions underlying user feedback. As a result, important aspects of user experience, such as frustration related to technical issues or satisfaction with content accessibility, may not be fully captured.

Given these limitations, there is a need for an approach that not only classifies sentiment but also explores the emotional characteristics of user reviews. By incorporating both sentiment and emotional analysis, a more comprehensive understanding of user perception can be achieved, particularly in identifying specific areas for service improvement in digital library applications.

METHODS

This study employs a sentiment analysis approach to examine user reviews of the iPusnas application obtained from the Google Play Store. Sentiment analysis is a sub-field of natural language processing (NLP) that focuses on identifying and analysing subjective information such as opinions, emotions, and attitudes, which are typically classified into positive, negative, or neutral categories (Usha & Dharmanna, 2021). This approach was selected to enable systematic interpretation of user-generated textual data, particularly in contexts where labelled training data are limited.

Data Collection

The dataset consists of 500 user reviews collected through a web scraping process using Google Collab from 2024 to May 2025. The extracted data include username, rating score, timestamp, and review text. These reviews represent spontaneous user feedback and serve as the primary source for analyzing user perception of the application.

Data Preprocessing

Prior to analysis, the dataset was processed to improve consistency and reduce noise.

The preprocessing stage included several steps:

- (1) text normalization through lowercasing,
- (2) tokenization by splitting sentences into individual words,
- (3) removal of stop words using an Indonesian stop word list,
- (4) stemming or lemmatization to obtain base word forms, and
- (5) removal of punctuation and numerical characters.

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These steps were applied within the orange data mining environment, which provides a visual workflow interface to organize preprocessing and analysis stages systematically.

Sentiment and Emotion Analysis Using SentiArt

Sentiment analysis in this study was conducted using the SentiArt method, a lexicon-based approach that calculates affective scores based on semantic similarity between words and predefined emotional dimensions, such as happiness, anger, fear, and sadness. Unlike conventional polarity-based methods, SentiArt enables the identification of emotional tendencies within textual data, providing a more nuanced understanding of user perception.

The implementation of SentiArt and subsequent classification processes were carried out within Orange using a structured workflow of interconnected analytical components (widgets). Based on the computed affective scores, each review was classified into one of three sentiment categories: positive, negative, or neutral.

The use of SentiArt was motivated by its ability to capture both sentiment polarity and emotional dimensions without requiring labeled training data, making it suitable for exploratory analysis. However, it is important to note that SentiArt was originally developed for English-language data. Its application to Indonesian-language reviews in this study relies on semantic similarity mechanisms, which allow cross-linguistic approximation but may affect classification accuracy. This limitation is acknowledged and considered in interpreting the results.

Model Evaluation

To assess the reliability of sentiment classification, model evaluation was conducted using a confusion matrix generated through the Test & Score procedure in Orange. Performance metrics include precision and recall for each sentiment category. Precision indicates the accuracy of predictions within a class, while recall reflects the model's ability to correctly identify all relevant instances.

The evaluation process employed stratified random sampling, where the dataset was proportionally divided into training and testing subsets to ensure balanced representation of sentiment classes.

Supplementary Analysis

To enrich the interpretation of findings, additional analyses were conducted within Orange. Word cloud visualization was used to identify dominant terms in the dataset, providing insight into frequently discussed issues. Topic modeling was applied to detect recurring themes in user reviews, while distribution analysis was used to examine patterns in sentiment scores and user ratings. A summary of the dataset, preprocessing stages, and analytical procedures is presented in Table 1, while the overall analytical workflow is illustrated in Figure 1.

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TABLE 1.
Data Structure and Analysis Process

No.	Stage	Description	Tools	Output
1.	Data Collection	Scraping 500 iPusnas user reviews from Google Play Store	Google Collab	Raw dataset in CSV format
2.	Data Structural	Downloaded dataset consists of username, score, timestamp (at), and review content	Orange	More structured dataset
3.	Preprocessing	Lowercasing, tokenization, stop word removal, punctuation removal, and lemmatization	Orange (preprocess text)	Clean dataset
4.	Sentiment Analysis	Calculation of emotion scores using the SentiArt method	Orange (SentiArt)	Sentiment scores and classification (positive, negative, neutral)
5.	Model Evaluation	Model evaluation using confusion matrix to obtain precision and recall	Orange (Test & Score)	Precision and recall values
6.	Data Visualization	Word cloud, heatmap, bar plot, distributions, and topic modeling	Orange	Visualizations of iPusnas user review analysis

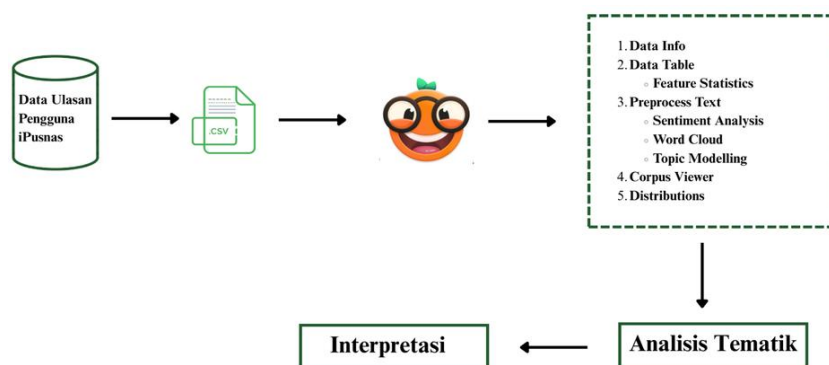


Figure 1. Steps of Analysis (Researcher)

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RESULT AND FINDINGS

Dataset Preparation

userName	score	at	content
Bening Ar	1	2024-01-01 21:24:44	tiba-tiba eror ga bisa minjam buku. padahal, jarang stock bukunya yang
Farah..	1	2024-01-01 21:44:12	Aplikasi kocak, udah daftar, tapi nggk bisa pinjam buku,, gimana mau ba
Aam Nour	1	2024-01-01 23:42:36	Aplikasi nya eror tidak bisa pinjem buku
Ayya Hida	1	2024-01-02 00:17:57	secara tiba-tiba tidak bisa meminjam karena error, semua fiturnya juga l
Mira Mela	1	2024-01-02 01:09:03	lpusnas di download kembali malah mengecewakan,,,gak ada buku yar
Mr M Gru	1	2024-01-02 01:25:09	Sering bug app nya
Yulia Chyr	1	2024-01-03 10:27:10	Gak rekomend
Suharni S	1	2024-01-04 03:18:51	Jelek 🤬🤬🤬 koneksi lancar malah gak bisa masuk
Ichamatch	1	2024-01-04 04:19:51	apk nyaa anehh, login aja gak bisaa kocak sekali, manaa maintenance la
Isma Huw	1	2024-01-04 11:20:27	Susah banget cuman mau baca buku. terus gimana coba verifikasi emai
Rara	1	2024-01-04 12:01:00	saya kesulitan untuk daftar akun di aplikasi ini, tolong bantuan nya. Teri

Figure 2. Research Dataset (Source: Researchers' own work with Orange Data Mining)

Preparation began with scraping data using Google Collab. The data scraped consisted of user reviews of iPusnas uploaded on Google Play Store. Figure 3 shows the dataset after being imported into the orange application, consisting of four columns: username, score, at, and content. The scraped data totaled 500 reviews meeting the criteria for relevant reviews. The data was downloaded in CSV format.

Corpus

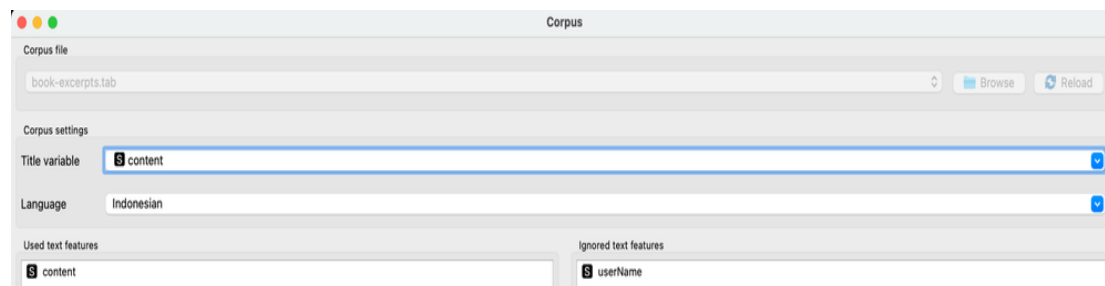


Figure 3. Corpus File (Source: Researchers' own work with Orange Data Mining)

After the dataset was imported into CSV format, the next step was to interpret the text data obtained from Google Collab. The corpus widget was used as a reference for further analysis such as tokenization, word extraction, and others. The corpus was formed to convert free text data into a more structured format processable by *machine learning models*. Since the scraped review data is in Indonesian, the language used in this corpus is also Indonesian.

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submitted by iPusnas users. This is consistent with the findings of Sayyed et al. (2021) who reveal that text analysis not only identifies sentiment polarity but also categorizes emotions such as joy, classified as positive sentiment, while fear and disgust tend to be classified as negative. Meanwhile, the neutral sentiment label shows no dominant emotion pattern, as the emotions expressed tend to be flat or unexpressive. This suggests that neutral-toned reviews are informational in nature without a particular emotional expression.

		Predicted			Σ
		negative	neutral	positive	
Actual	negative	18	67	5	90
	neutral	1	9	0	10
	positive	0	43	27	70
Σ		19	119	32	170

Figure 5. Confusion Matrix (Source: Researchers' own work with Orange Data Mining)

The evaluation results show that the model achieves high precision on the negative class (94.7%) and positive class (84.4%), indicating that the model's predictions are relatively accurate on both classes. However, the recall values for the negative class (20%) and positive class (38.6%) indicate that the model has not been able to identify all data belonging to those categories. It should be noted that the precision and recall values reported here are per-class values, not overall model averages.

The low recall values may occur because the model incorrectly categorizes negative and positive data into the neutral category. This also impacts the low precision of the neutral class (7.6%). This condition may be caused by the model's limitations in understanding Indonesian language context, particularly regarding meaning or expression variations used in reviews by iPusnas users. Furthermore, the model's shortcomings in handling stop words, tokenization, or lemmatization may reduce model performance due to class imbalance in sentiment data, thereby affecting precision and recall metrics. This is consistent with the findings of Prajapati (2025) who states that the text processing methods and techniques chosen can influence the performance of sentiment analysis.

Based on Figure 8, the word "buku" (book) is the most dominant word in user reviews, indicating that the application is used as a reading medium. Additionally, positively toned words reflecting user satisfaction appear in the reviews, such as "bagus" (good), "nyaman" (comfortable), and "bermanfaat" (beneficial). This is consistent with Ayuningtiyas et al. (2025) who state that the appearance of the keyword "book" indicates iPusnas's success in meeting users' basic needs for access to digital literature.

Moreover, the word cloud analysis also reveals negatively toned user reviews such as *jelek* (bad), *lemot* (slow), *update*, *lambat* (slow), *error* (error), and others, referring to technical issues experienced by users. This aligns with the findings of Rahmajati et al. (2025) who found that words such as error, bad, and update generally represent user dissatisfaction with the application. Based on the above, it can be concluded that user reviews vary widely, from satisfaction and disappointment with the application to future hopes for iPusnas.

3) Topic Modeling

Topic	Keywords	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
1	barang, buku, baca, koleksi, ...	1.20818	0.86133	-0.81934	-1.1871	-0.33337	-0.33794	0.58887	0.07764	-1.38889	-0.4
2	error, lambat, update, ...	0.20069	-0.46332	-0.53141	-0.80959	0.21749	0.18503	-0.22954	-0.16482	-0.34788	-0.007
3	bagus, nyaman, bermanfaat, ...	1.02026	0.19085	0.064236	0.16482	0.08719	-0.11989	0.057099	0.12925	-0.346434	0.74
4	aplikasi, user, ...	0.049933	-0.07787	-0.045802	0.017296	0.008707	-0.027385	0.018206	0.18164	-0.007528	-0.048
5	cepat, ringan, ...	0.340333	-0.81442	-0.74054	-0.54544	-0.77282	0.44924	0.29339	0.099249	-0.21301	-0.06
6	mudah, ...	0.17734	-0.23864	-0.19373	0.20157	0.37888	0.19326	-0.15483	-0.20864	-0.81238	-0.19
7	Yulia Chandra, ...	0.252671	-0.37825	-0.24054	0.41634	-0.44668	0.10247	-0.49012	-0.33450	-0.28269	0.52
8	Suharto, ...	0.20991	-0.39003	-0.38707	0.42309	0.27591	-0.35036	-0.16492	0.35630	-0.37002	-0.40
9	Wahana, ...	0.27795	-0.58466	0.78035	-0.04349	-0.04263	0.21622	0.28827	0.20160	-0.00202	-0.13
10	Heri, ...	0.84897	0.30072	-0.04063	0.10484	0.027919	-0.01189	0.1129	-0.06284	-0.19333	-0.20
11	Roni, ...	0.27843	0.10848	0.49311	-0.03927	0.27427	0.16864	-0.15868	0.01793	0.13306	0.24
12	Sri Ari, ...	0.071503	-0.029848	-0.025068	-0.010795	0.11494	0.042011	0.0283458	-0.11478	-0.024756	-0.09
13	Maryati, ...	1.05832	0.17437	0.25229	-0.099723	-0.07621	0.041834	-0.042098	-0.07821	-0.004696	0.36
14	Dhoni Nurul, ...	0.031243	-0.11269	0.037648	0.02783	0.041911	-0.059743	0.15135	-0.04022	0.018134	-0.071
15	Asih Fatmahaningrum, ...	1.5211	0.039986	-0.33745	-0.75129	-0.078486	-0.072497	0.222081	0.34832	-0.12487	0.077
16	Umanah, ...	0.50432	-0.07987	-0.16178	-0.19178	-0.15986	0.0091026	0.18162	0.28196	-0.16664	-0.26
17	Fadli, ...	0.264361	-0.81543	-0.52844	0.53774	0.30427	-0.64293	0.051495	0.37016	0.44015	-0.048
18	Jenny, ...	0.43054	-0.82616	-0.26914	0.33793	1.2441	0.058414	-0.55375	-0.20201	-0.81004	0.29
19	Tiya Zahra, ...	0.181733	-0.10643	-0.070232	0.089586	0.34347	0.014903	-0.47799	-0.28327	-0.28168	-0.2
20	Rita Darmasari, ...	1.28027	1.23409	-0.13387	0.15983	0.02709	0.364799	-0.13784	-0.12194	0.10293	-0.36
21	Nuzul Nuzul, ...	0.15123	-0.27518	-0.14519	0.10715	0.21358	0.017749	-0.021821	-0.01771	-0.021962	-0.1
22	Iri, ...	0.70549	-1.24226	-0.69066	-0.25682	1.16886	0.166776	-1.35076	1.55498	1.18629	0.24
23	Hendri, ...	0.872624	-1.3227	0.00016622	0.19486	-1.1132	0.19127	0.37093	0.38844	0.18796	0.65
24	Herma, ...	2.00726	0.64242	-0.012929	0.22858	-0.10083	0.21584	-0.092386	-0.23242	-0.071945	0.24
25	Agus, ...	0.248891	-0.52497	-0.16979	-0.05068	0.09933	0.00976	-0.48162	-0.16421	-0.020696	1.2
26	Rambung, ...	1.38737	-0.98975	-0.61821	-1.88308	0.21644	0.458374	-0.33837	0.05900	0.01051	0.72
27	Muhammad, ...	1.27987	-0.86287	0.78936	-0.029689	0.043848	0.126821	0.16422	-0.0027807	0.057418	-0.20
28	Nisa, ...	0.333782	0.26476	0.276984	0.10467	0.27629	0.318271	-0.16112	0.23272	0.21341	0.21
29	Suci, ...	1.48296	-0.69921	0.58271	0.164795	0.164729	-0.121271	-0.41308	0.06383	-0.14559	0.63
30	Martani, ...	0.024879	-0.04445	-0.04741	0.0012016	-0.0012016	-0.0012016	-0.0012016	0.0012016	0.0012016	0.11
31	Arif, ...	1.00786	0.38055	-0.089744	0.043412	0.34721	0.481029	-0.13907	-0.023023	0.34718	-0.15
32	Sari, ...	1.82179	-0.34891	0.19124	-0.03391	0.19126	0.20996	-0.44664	0.097275	0.13668	-0.11
33	Kompilasi, ...	2.97226	0.86879	-0.34335	-0.09234	1.0471	1.0657	-0.06529	-0.06529	0.081445	0.030
34	Asih, ...	2.9667	0.12718	1.07071	0.003801	-0.089174	0.003801	0.284826	-0.0684	0.101486	0.048
35	Martani, ...	1.14181	0.11178	0.058686	-0.32102	-0.17203	-0.050174	-0.18113	-0.02022	-0.00335	1.3

Figure 3. Top Modeling (Source: Researchers' own work with Orange Data Mining)

The analysis results indicate that there are several main topic groups that constitute the substance of user reviews. Based on Figure 8, it is known that there are 10 topic models emerging in the user review dataset, with different topic dominance for each row, such as row one being dominated by topic 1 while row 22 is dominated by topic 5.

Based on analysis of dominant keywords appearing in each topic, at least 3 main clusters can be identified. First, topics related to the application's core function as a reading medium, marked by words such as "buku" (book), "baca" (read), and "koleksi" (collection). Second, topics related to technical application issues, marked by words such as "error" (error), "lemot" (slow), "update", and "lambat" (slow). The third topic relates to user hopes and suggestions, marked by words such as "harap" (hope), "tolong" (please), and "diperbaiki" (fix/improve).

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These findings confirm that technical issues represent a recurring and structured theme in user reviews. Furthermore, this reflects that users not only evaluate the application's features and core functions but also other aspects such as service quality, system performance, and ease of use. This diversity signals to the National Library the need to improve overall system quality, not only in terms of content provision but also in technical aspects to enhance user experience.

4) Corpus Viewer



Figure 4. Corpus Viewer (Source: Researchers' own work with Orange Data Mining)

The corpus viewer was used to display and validate the results of the preprocessing stage. In this study, the corpus viewer employs a *bag of words* representation visualized using *feature statistics*. Based on the visualization in Figure 10, the word "*buku*" (book) is the most frequently occurring word with a mean of 0.924, followed by the words "*bagus*" (good), "*baca*" (read), and "*update*".

The dominance of the word "*buku*" with a mean close to 1 indicates that almost all reviews confirm that iPusnas's identity as a reading application has been successfully communicated and perceived by its users, providing a positive signal to the National Library that the application's primary purpose and function are well understood.

Meanwhile, the considerable variation in mean values between words reflects an uneven distribution in user reviews. This condition arises because users tend to address only specific topics relevant to their own experience. This indicates that the *bag of words* approach is capable of capturing dominant patterns but risks missing contextual nuances.

Distributions

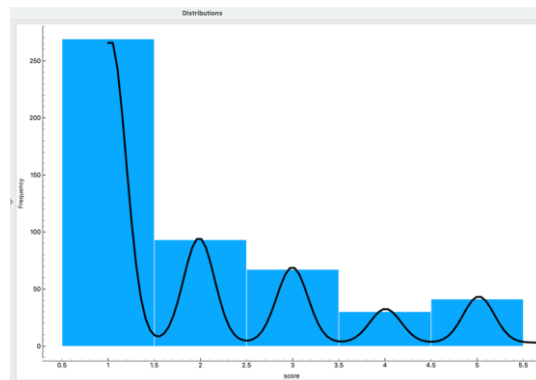


Figure 5. Distributions (Source: Researchers' own work with Orange Data Mining)

The research findings indicate that the score distribution pattern is not normal, with multiple peaks, where the highest peak occurs at the lowest score. Based on Figure 11, the score distribution pattern is not normal as it has multiple peaks, with the highest peak at score 1. This indicates a tendency toward negative assessments of the application by some iPusnas users.

Furthermore, the KDE curve shows inconsistent ratings among iPusnas users, resulting in variability in the KDE curve. Based on this distribution, it is known that the majority of reviews or ratings given by iPusnas users lean toward the negative, while some indicate problems in the application, but a satisfied segment still exists (score 5). This variation suggests that there are significantly different experiences among application users. This aligns with Patil et al. (2023) who state that user reviews have an imbalanced distribution, causing minority classes of either positive or negative sentiment to be underrepresented, resulting in difficulty for the model to classify reviews accurately.

CONCLUSIONS

This study aimed to examine the sentiment of iPusnas application users based on 500 reviews submitted on Google Play Store using the orange platform with the SentiArt method. Based on the research findings, there are three main conclusions.

In terms of emotion, the *happiness* dimension dominates positive sentiment, indicating that the majority of application users express their satisfaction with the application. Meanwhile, emotions of *fear*, *anger*, and *disgust* tend to dominate negative sentiment, signifying that user dissatisfaction is expressed with stronger and more varied emotional content.

Second, the evaluation results using the confusion matrix show that the model achieves high precision on the negative and positive classes; however, the low recall values indicate that many negative and positive reviews submitted by users were misclassified and grouped as neutral. This condition occurs because SentiArt has limitations in understanding the Indonesian language and due to imbalanced data distribution across sentiment groups. Meanwhile, word

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cloud and topic modeling analyses consistently reveal two sides of the user experience: satisfaction with iPusnas's core function as a reading medium, and complaints related to technical issues.

Additionally, this study demonstrates that the Orange visual platform can be utilized as an effective alternative for sentiment analysis, particularly for researchers without programming skills.

Recommendations for the National Library

1. The National Library is expected to optimize application performance, particularly regarding application speed and stability, as the analysis results show that many negative reviews relate to technical issues such as slow performance, errors, and lag.
2. The National Library is expected to update its collection, as the analysis of user reviews revealed the words "update" and "collection," indirectly indicating complaints and user expectations regarding the availability of more relevant and diverse collections.
3. The National Library is also expected to actively respond to user feedback regarding the iPusnas application, as the analysis of user reviews reveals that users not only comment on and praise the application but also express their hopes for iPusnas to improve in the future.

AUTHOR CONTRIBUTIONS

[Rezi Anjelia Putri]: Conceptualization, methodology, data collection, data analysis, writing the original draft, and editing. [Muhamad Prabu Wibowo]: Supervision, validation, review and editing.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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