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Enhancing Library Services Through User Response Analysis Based on Twitter Data Using Aspect Based Sentiment Analysis (ABSA)

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ABSTRACT

Social media has become an essential part of everyday communication, including within the library context. Twitter, in particular, provides an Application Programming Interface (API) that enables real-time and comprehensive text-mining analyses of users' perceptions and experiences. This study examines efforts to enhance library service quality by identifying and interpreting user sentiments on Twitter in a more detailed manner, enabling libraries to formulate targeted and effective service improvement strategies. The research consists of several stages: a literature review on sentiment analysis, data collection from Twitter using API-based data crawling, and a series of pre-processing steps, including data cleaning, case folding, tokenization, numerization, stopword removal, and stemming. Data were analyzed using the Aspect-Based Sentiment Analysis (ABSA) method. The findings indicate that the Collection and Facilities aspects receive the highest levels of positive sentiment, while Accessibility and Service attract considerable negative sentiment, signaling priority areas for improvement. Based on these results, libraries may consider extending operational hours, improving digital access, updating collections, and renovating facilities. Additionally, strengthening staff competencies and interpersonal skills is crucial for improving service quality and increasing user satisfaction.

Keywords: Library service; User experience; Sentiment analysis; Aspect Based Sentiment Analysis (ABSA)

1. INTRODUCTION

Libraries play a vital role in higher education institutions in enhancing the quality of education through reading literacy (Rafiq et al., 2021). In the context of higher education, libraries provide book lending services accessible to all university members, including faculty, students, and staff (Ifada et al., 2019). According to Law No. 43 of 2007 concerning Libraries, a library is defined as an institution that professionally manages a collection of written, printed, and recorded works using standardized systems to meet the needs of education, research, preservation, information, and recreation. Every higher education institution, both public and private, is required to maintain a library that provides the necessary services and facilities for its users.

University libraries serve not only as providers of educational resources but also as learning centers that support the academic and professional development of the entire academic community. Through well-organized print and digital collections, as well as trained staff who curate and assist users in accessing necessary resources, academic libraries function as vital learning hubs (Rahayu, 2017). herefore, librarians must continuously adapt to evolving user needs to ensure the quality of services remains high. Consequently, libraries must consistently update their collections and improve services. Since users, especially students, seek easily accessible and relevant information, libraries must be able to meet these expectations to maintain high-quality standards (Maulana, 2016).

In the modern era, libraries also face increasing pressures from digitalization. Social media has become an integral part of daily life, including within the library context. Twitter, as a microblogging platform, enables rapid dissemination of news and information through concise messages. With a significant number of Twitter users in Indonesia, the platform offers an effective channel for capturing public opinion on various topics (Rizaty, 2022). Twitter also provides an Application Programming Interface (API) that allows automated access to user profiles, follower data, and tweets (Trupthi et al., 2017). Based on this description, sentiment analysis using Twitter can be leveraged in the library context to understand users' perceptions and experiences in a real-time and comprehensive manner.

Using Twitter as a data source offers valuable opportunities for libraries to employ data-mining techniques, which involve extracting meaningful patterns, information, and knowledge from large volumes of unstructured data. In the library context, sentiment analysis or opinion mining is used to understand, extract, and process text data automatically to obtain information about the sentiment expressed in user statements (Tandel et al., 2019). This sentiment analysis enables libraries to determine whether user sentiment is positive, negative, or neutral, and to identify the specific aspects that trigger these sentiments (Mowlaei et al., 2020).

The quality of library services is heavily dependent on user satisfaction assessments, which determine whether user needs are being met. Therefore, as an effort to continuously monitor and improve service quality, this study introduced an innovation by utilizing Aspect-Based Sentiment Analysis (ABSA) to analyze library user sentiments based on Twitter data. This method represented a relatively unexplored approach within the context of Indonesian libraries. ABSA not only identified the overall sentiment (positive, negative, or neutral) but also revealed the specific aspects that were the subjects of sentiment, such as Accessibility, Collection, Facilities, and Service which are critical components of library management. These four key aspects served as the foundation for improving library services, as they directly influenced user experience and satisfaction.

Thus, the specific goal of this study was to enhance the quality of library services by identifying and understanding user sentiments in greater detail through Twitter, enabling libraries to develop more targeted and efficient improvement strategies. This was expected to address the increasingly high and diverse expectations of users and to enhance their satisfaction and engagement in utilizing library services.

In detail, the ABSA method offered a more refined analysis compared to general sentiment analysis. It enabled libraries to pinpoint specific service aspects that required improvement, as well as those that were performing well and should be maintained or further strengthened. This research held significance not only for Indonesian libraries but also for libraries globally, as optimizing services remains a universal challenge in the digital age. Effective library services today must go beyond merely offering a wide collection of books; they must also address user experience in areas such as facility comfort (Facilities), service efficiency and staff friendliness (Service), and digital system accessibility (Accessibility). By implementing ABSA-based sentiment analysis, libraries could continuously adapt and improve their services, providing a more personalized and satisfying user experience. This approach aligned with the global trend of enhancing user engagement through data-driven service management, making it applicable across different regions and contexts.

2. METHODS

The initial step of this research involved reviewing relevant literature on sentiment analysis, particularly focusing on Aspect-Based Sentiment Analysis (ABSA) and its applications in text mining. Sentiment analysis, as explored by Pang et al. (2002), allowed for the extraction of sentiments from textual data, identifying the polarity of opinions and categorizing them into positive, negative, or neutral sentiments. Similarly, Turney (2002) contributed a novel unsupervised approach, proposing the use of semantic orientation to determine the positivity or negativity of a review by analyzing adjectives and adverbs. This method, despite its simplicity, proved effective across multiple domains with varying degrees of accuracy, offering an alternative approach for sentiment analysis where labeled data was scarce.

The second step was data collection from Twitter, which employed data crawling techniques to gather responses from library users through the Twitter API (Ma, 2021). The initial dataset consisted of 256 data points, which were filtered based on their relevance to library services and their focus on the four key aspects: Accessibility, Collection, Facilities, and Service. The collected data underwent several pre-processing stages, as illustrated in Figure 1.

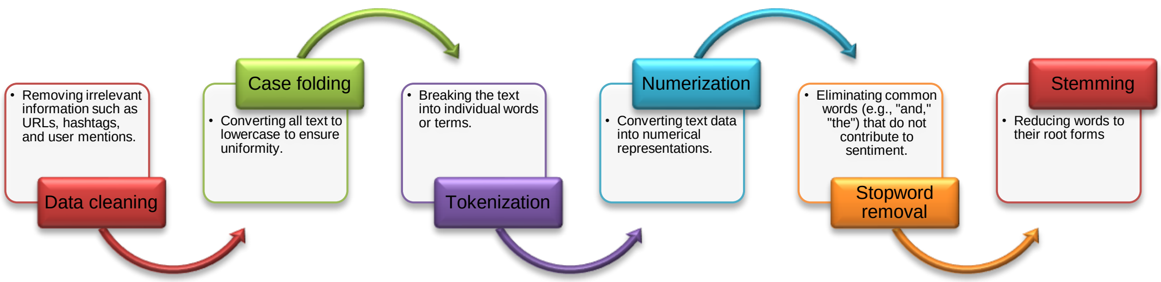

Figure 1. Flowchart of data collection
(Hidayatullah & Ma'arif, 2017; Juna & Hayaty, 2023)

After pre-processing, feature extraction was performed using the Term Frequency-Inverse Document Frequency (TF-IDF) method, widely used in text mining to evaluate the significance of a word in a document relative to a collection of documents or corpus (Sparck Jones, 1972). This method assigned higher weight to terms that appeared frequently in a particular document but are less common across the corpus, highlighting their relative importance in distinguishing text content (Jalilifard et al., 2021).

Additionally, the Natural Language Toolkit (NLTK) was utilized for various text processing tasks, including tokenization, stop-word removal, and stemming. NLTK provided a suite of libraries and programs that facilitated the handling of human language data, which wass essential for effective sentiment analysis. Following feature extraction with TF-IDF, Latent Dirichlet Allocation (LDA) was applied for topic modeling. LDA is a generative statistical model that assumes documents are mixtures of topics and that each topic is characterized by a distribution over words. By applying LDA, it can identify underlying themes in the library service feedback, enriching our understanding of user sentiments and opinions.

After pre-processing, it was found that not all initial data points were usable. Therefore, this research selected only data relevant to library services that focused on the four aspects mentioned above. The total usable dataset comprised 256 data points. The data resulting from TF-IDF feature extraction were then processed using the ABSA model to classify user sentiment as positive, neutral, or negative toward library services. The ABSA model also identified key aspects associated with each sentiment classification, which could be used as discussion points for improving the quality of library services.

To further enhance the sentiment classification, Logistic Regression and Long Short-Term Memory (LSTM) models were utilized. Logistic Regression served as a straightforward yet powerful statistical method for binary and multi-class classification tasks, providing interpretable results and quick training times. In contrast, LSTM is a type of recurrent neural network that was particularly effective for sequence prediction tasks, making it well-suited for analyzing sentiment in text data that contained contextual dependencies. The LSTM model was able to capture long-term dependencies in the data, improving the accuracy of sentiment classification compared to traditional methods.

The ABSA model also identified key aspects associated with each sentiment classification, which were used as discussion points for improving library service quality. By integrating these various methods, TF-IDF, LDA, NLTK, Logistic Regression, and LSTM, it aimed to achieve a comprehensive analysis of user sentiments, ultimately informing enhancements to library services.

3. RESULTS AND DISCUSSION

This research analyzes the enhancement of library services through the social media platform Twitter. The first stage involved crawling Twitter data using the API. Data was collected from May 12, 2024, to May 17, 2024, with a total of 1,250 data points.

	text	aksesibilitas	Unnamed: 2	koleksi	Unnamed: 4	fasilitas	Unnamed: 6	pelayanan	Unnamed: 8
0	NaN	positif	negatif	positif	negatif	positif	negatif	positif	negatif
1	-ness titipan guys, mau tanya dong di perpusta...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	Sepanjang bulan ini kami mengajak Anda semakin...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	Senin, 13 Mei 2024\n\nPromosi Perpustakaan mel...	NaN	NaN	NaN	NaN	1	0	NaN	NaN
4	boycotting is easy guys, dulu aku kalau nugas ...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...
1245	Selamat atas tersertifikasinya 8 RPTRA dan Per...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1246	Dulu dekat kos SMA ada perpustakaan desa kecil	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1247	iya ya kapan ya ada perpustakaan daerah yang b...	0	1	NaN	NaN	NaN	NaN	NaN	NaN
1248	Perpustakaan Surga benar-benar komik yang isti...	NaN	NaN	1	0	NaN	NaN	NaN	NaN
1249	Dalam setiap halaman buku yang kami sentuh	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

1250 rows × 9 columns

Figure 2. Results of Twitter data crawling

The next stage in this research is the dataset labeling process. The ABSA model focuses not only on sentiment analysis of the text but also on the aspects contained within it. This study identifies four key aspects in efforts to improve library services: Accessibility, Collection, Facilities, and Service. In the Accessibility aspect, positive cases are represented by libraries with multiple branches across various city areas, offering flexible operating hours, including weekends and holidays, and providing online library services that allow access to digital collections from anywhere. Conversely, negative cases include libraries located in areas that are difficult to reach by public transportation with limited operating hours, making them challenging for the local community to access.

For the Collection aspect, positive cases are characterized by libraries that have a diverse and up-to-date book collection, covering various genres and topics that appeal to different age groups and interests. Conversely, negative cases involve libraries with outdated collections or those limited to specific topics or genres, which do not meet the diverse needs of readers.

Regarding the Facilities aspect, positive cases include libraries that offer modern and comfortable amenities, such as well-lit and spacious reading areas, discussion or meeting rooms, children's play areas, and disability-friendly accessibility. Negative cases, on the other hand, involve libraries with poorly maintained, dirty, or uncomfortable facilities for visitors, such as insufficient seating, poor lighting, or non-functional amenities.

Lastly, in the Service aspect, positive cases are marked by library staff who are friendly, skilled, and ready to assist visitors in finding the resources they need, as well as providing efficient and responsive lending services. On the other hand, negative cases include a lack of trained staff or staff who are unfriendly and unhelpful, as well as slow or inefficient lending services, which can diminish the quality of the library user experience.

Based on the description above, each data point will be labeled as Positive, Negative, or Neutral if it does not fit either category. After labeling the dataset, it was found that not all data could be used. This research only selects data related to library services that focus on the four aspects mentioned above. Therefore, the total usable dataset comprises 256 data points. Table 1 provides detailed information on the number of labeled datasets.

Table 1. Labeling dataset

Label Aspect	Number of Data
facilities	87
accessibility	79
collection	45
service	26
collection, facilities	10
accessibility, collection	3
facilities, service	3
accessibility, collection, facilities	3
Total	**256**

Based on the information above, it shows that the data labeling is multi-label, where data can have 1 to 3 aspect labels.

Table 2. Multi-labeling data set

Aspect	Sentiment	Number of Data
Accessibility	Positive	50
	Negative	35

Aspect	Sentiment	Number of Data
Collection	Positive	50
	Negative	11
Facilities	Positive	89
	Negative	14
Service	Positive	21
	Negative	8

Based on the series of data findings above, the aspects of facilities and collection received the highest appreciation from users; however, accessibility and service also need improvement to enhance the library user experience. Therefore, several recommendations can be made, including expanding operational hours (Migdalski & Moreau, 2021) and improving access (Ezell et al., 2022), conducting routine updates to the book collection to align with current trends and reader needs (Hambarde, 2023), and renovating and maintaining facilities for visitor comfort (Hough & Pomputius, 2022). Additionally, staff training to improve skills and friendliness is also crucial for enhancing the quality of library services.

In line with the research objectives, which are to assess the quality of library services through user responses from Twitter using Aspect-Based Sentiment Analysis (ABSA) and to improve library service quality based on sentiment analysis results, Twitter data crawling using the API has been conducted, followed by dataset labeling using the ABSA model. This model not only identifies the sentiment of each tweet but also the specific aspects related to library services, namely accessibility, collection, facilities, and service, as detailed in the previous findings (Table 1).

The sentiment data findings in Table 2 show the distribution of data and sentiment across each aspect, providing a comprehensive view of user perceptions regarding library services. For example, the aspects of facilities and collection received the highest positive sentiment, indicating that users appreciate the diversity of the book collection and the comfortable facilities. However, there are also aspects that received negative sentiment, such as accessibility and service, highlighting areas that need improvement.

At this stage, the study has obtained a list of sentiment data along with corresponding recommendations. By linking these two elements, the study not only provides an understanding of the current quality of library services but also offers practical solutions for future improvements. This approach ensures that library service enhancements are based on data and direct user feedback, making them more relevant and effective.

The next phase in this research is Data Preprocessing. This process involves several crucial steps. The first step is lowercasing, which converts all text characters to lowercase to ensure consistency and reduce word variation due to differences in uppercase and lowercase usage (Gao & Qi, 2023). This is important because text processing algorithms often consider "Buku" and "buku" as distinct entities. In the provided data, all text from tweets related to the library has been converted to lowercase, enabling more accurate analysis by the ABSA algorithm.

Table 3. Data after lowercasing

No	Original Text	Result	Translate English
1	Alasan Saya Kecewa dengan Perpustakaan UI, Jam Operasional Nggak Jelas hingga Koleksi Ilang-ilangan #TerminalMojok https://t.co/JWKlhzeWJW	alasan saya kecewa dengan perpustakaan ui, jam operasional nggak jelas hingga koleksi ilang-ilangan #terminalmojok https://t.co/jwklhzewjw	my disappointment with the ui library is due to unclear operating hours and missing collections #terminalmojok https://t.co/jwklhzewjw
2	pertama kali mengalami insiden tak terduga : uang gue dicuri di loker perpustakaan□□□□□□ mana lokernya juga tipe loker yang ga ada kuncinya, asli sih gue sedih banget, ga expect mengalami hal seperti ini	pertama kali mengalami insiden tak terduga : uang gue dicuri di loker perpustakaan□□□□□□ mana lokernya juga tipe loker yang ga ada kuncinya, asli sih gue sedih banget, ga expect mengalami hal seperti ini	for the first time, I experienced an unexpected incident: my money was stolen from the library locker □□□□□□ and the locker was the kind that didn't have a lock. honestly, I'm really sad, I didn't expect to go through something like this

The next step involves removing URLs and hashtags to ensure that the analysis focuses on the relevant text content without being disrupted by external links and hashtags, which often do not provide additional information related to the sentiment or aspects being analyzed. By removing URLs and hashtags, the text data becomes cleaner and more focused, allowing the ABSA algorithm to more effectively identify patterns and sentiments contained within the text.

Table 4. Data after removing URLs and Hashtags

No	Original Text	Result	Translate English
1	Alasan Saya Kecewa dengan Perpustakaan UI, Jam Operasional Nggak Jelas hingga Koleksi Ilang-ilangan #TerminalMojok https://t.co/JWKlhzeWJW	alasan saya kecewa dengan perpustakaan ui, jam operasional nggak jelas hingga koleksi ilang-ilangan	my disappointment with the ui library is due to unclear operating hours and missing collections
2	pertama kali mengalami insiden tak terduga : uang gue dicuri di loker perpustakaan□□□□□□ mana lokernya juga tipe loker yang ga ada kuncinya, asli sih gue sedih banget, ga expect mengalami hal seperti ini	pertama kali mengalami insiden tak terduga : uang gue dicuri di loker perpustakaan□□□□□□ mana lokernya juga tipe loker yang ga ada kuncinya, asli sih gue sedih banget, ga expect mengalami hal seperti ini	for the first time, I experienced an unexpected incident: my money was stolen from the library locker □□□□□□ and the locker was the kind that didn't have a lock. honestly, I'm really sad, I didn't expect to go through something like this

The next step involves removing numbers and symbols to ensure that the text analysis focuses on relevant verbal content without being disrupted by numbers and symbols, which often do not contribute meaningfully to sentiment or aspect analysis.

Table 5. Data after Removing numbers and symbols

No	Original Text	Result	Translate English
1	Alasan Saya Kecewa dengan Perpustakaan UI, Jam Operasional Nggak Jelas hingga Koleksi Ilang-ilangan #TerminalMojok https://t.co/JWKlhzeWJW	alasan saya kecewa dengan perpustakaan ui jam operasional nggak jelas hingga koleksi ilangilangan	my disappointment with the ui library is due to unclear operating hours and missing collections
2	pertama kali mengalami insiden tak terduga : uang gue dicuri di loker perpustakaan□□□□□□ mana lokernya juga tipe loker yang ga	pertama kali mengalami insiden tak terduga uang gue dicuri di loker perpustakaan mana lokernya juga tipe loker yang ga	for the first time, I experienced an unexpected incident: my money was stolen from the library locker and the locker was

No	Original Text	Result	Translate English
	ada kuncinya, asli sih gue sedih banget, ga expect mengalami hal seperti ini	ada kuncinya asli sih gue sedih banget ga expect mengalami hal seperti ini	the kind that didn't have a lock. honestly, I'm really sad, I didn't expect to go through something like this

The next step involves removing punctuation to simplify the text and ensure that the analysis focuses on relevant words without being influenced by punctuation that does not contribute meaningfully to understanding the sentiment or aspects being analyzed.

Table 6. Data after removing punctuation

No	Original Text	Result	Translate English
1	Alasan Saya Kecewa dengan Perpustakaan UI, Jam Operasional Nggak Jelas hingga Koleksi Ilang-ilangan #TerminalMojok https://t.co/JWKlhzeWJW	alasan saya kecewa dengan perpustakaan ui jam operasional nggak jelas hingga koleksi ilangilangan	my disappointment with the ui library is due to unclear operating hours and missing collections
2	pertama kali mengalami insiden tak terduga : uang gue dicuri di loker perpustakaan□□□□□□ mana lokernya juga tipe loker yang ga ada kuncinya, asli sih gue sedih banget, ga expect mengalami hal seperti ini	pertama kali mengalami insiden tak terduga uang gue dicuri di loker perpustakaan mana lokernya juga tipe loker yang ga ada kuncinya asli sih gue sedih banget ga expect mengalami hal seperti ini	for the first time, I experienced an unexpected incident: my money was stolen from the library locker and the locker was the kind that didn't have a lock. honestly, I'm really sad, I didn't expect to go through something like this

Slang word removal is also carried out to simplify and normalize the text, allowing the analysis to focus on relevant and formal content. Slang words often vary and lack consistent meaning, so removing or replacing them with more formal equivalents can assist the ABSA algorithm in understanding and identifying patterns and sentiments more accurately.

Table 7. Data after removing slang words

No	Original Text	Result	Translate English
1	Alasan Saya Kecewa dengan Perpustakaan UI, Jam Operasional Nggak Jelas hingga Koleksi Ilang-ilangan #TerminalMojok https://t.co/JWKlhzeWJW	alasan saya kecewa dengan perpustakaan ui jam operasional jelas hingga koleksi ilangilangan	my disappointment with the ui library is due to unclear operating hours and missing collections
2	pertama kali mengalami insiden tak terduga : uang gue dicuri di loker perpustakaan□□□□□□ mana lokernya juga tipe loker yang ga ada kuncinya, asli sih gue sedih banget, ga expect mengalami hal seperti ini	pertama kali mengalami insiden terduga uang dicuri di loker perpustakaan mana lokernya juga tipe loker yang ga ada kuncinya asli sih sedih banget ga expect mengalami hal seperti ini	this is the first time experiencing a suspected theft of money from a library locker, which also happens to be the type of locker without a key. honestly, it's really sad and unexpected to go through something like this

The removal of common words or stop words, such as " dan," " yang," "di," and "ke," is performed because these words often do not provide significant information for sentiment analysis. By removing stop words, the text becomes more concise and focused on keywords that carry higher informational weight.

Table 8. Data after removing stop words

No	Original Text	Result	Translate English
1	Alasan Saya Kecewa dengan Perpustakaan UI, Jam Operasional Nggak Jelas hingga Koleksi Ilang-ilangan #TerminalMojok https://t.co/JWKlhzeWJW	alasan kecewa perpustakaan ui jam operasional hingga koleksi ilangilangan	the reason for disappointment with the ui library is the operational hours, which have led to missing collections
2	pertama kali mengalami insiden tak terduga : uang gue dicuri di loker perpustakaan������ mana lokernya juga tipe loker yang ga ada kuncinya, asli sih gue sedih banget, ga expect mengalami hal seperti ini	mengalami insiden terduga uang dicuri loker perpustakaan lokernya tipe loker ga kuncinya asli sih sedih banget ga expect mengalami	experienced suspected incident money stolen library locker, type locker without key. really sad unexpected go through this

Finally, lemmatization is performed to convert words in the text to their base or lemma form, making them more consistent and easier for algorithms to analyze (Akhmetov et al., 2020). This step aims to reduce variations of different words that have the same meaning, thereby enhancing the accuracy of sentiment and aspect analysis. All these preprocessing stages assist in further processes such as tokenization, punctuation removal, and feature extraction for more in-depth sentiment analysis.

Table 9. Data after lemmatization

No	Original Text	Result	Translate English
1	Alasan Saya Kecewa dengan Perpustakaan UI, Jam Operasional Nggak Jelas hingga Koleksi Ilang-ilangan #TerminalMojok https://t.co/JWKlhzeWJW	alas kecewa pustaka ui jam operasional hingga koleksi ilangilangan	reason disappointment library ui operational hour lead to collection missing
2	pertama kali mengalami insiden tak terduga : uang gue dicuri di loker perpustakaan������ mana lokernya juga tipe loker yang ga ada kuncinya, asli sih gue sedih banget, ga expect mengalami hal seperti ini	alami insiden duga uang curi loker pustaka lokernya tipe loker ga kunci asli sih sedih banget ga expect alami	experience incident suspect money steal locker library, which be type locker without key. really sad not expect experience

In the context of this study, each preprocessing step has significant advantages. First, lowercasing and removing URLs, hashtags, numbers, and symbols help produce cleaner and more uniform data (Alshanik et al., 2020; HaCohen-Kerner et al., 2020), which is essential for text-based analyses like ABSA. Second, handling slang words and stop words ensures that only truly relevant words are analyzed (Aribowo et al., 2021; Permana, 2022), allowing the model to focus more effectively on pertinent aspects and sentiments. Finally, lemmatization ensures that different word variations are considered as the same entity, improving the accuracy of aspect and sentiment recognition in the text (Gogoi & Baruah, 2022).

Through these preprocessing stages, this study ensures that the data used in the ABSA analysis is clean, relevant, and well-structured. This allows the model to be more effective in identifying and analyzing the aspects and sentiments contained in user tweets, thus providing more accurate and in-depth insights into user perceptions of library services.

After completing several preprocessing steps, such as lowercasing, removing URLs and hashtags, removing numbers and symbols, and lemmatization, the next step is to test the

Aspect-Based Sentiment Analysis (ABSA) model. This testing aims to evaluate the model's performance in identifying and analyzing user sentiments towards various aspects of library services based on data from Twitter. The two primary approaches used in this testing are Logistic Regression and Long Short-Term Memory (LSTM). Each approach employs different methods and techniques for processing and analyzing text data.

The first approach, Logistic Regression, involves the use of Term Frequency-Inverse Document Frequency (TF-IDF) and a combination of TF-IDF with Latent Dirichlet Allocation (LDA). TF-IDF is a method used to assess the importance of a word within a document relative to the entire document collection (Jalilifard et al., 2021). LDA, on the other hand, is a technique used to discover hidden topics within a text corpus (Ravikumar et al., 2023). The combination of TF-IDF and LDA allows the model to capture more complex relationships between words and topics in the data (Dai et al., 2022).

The second approach uses Long Short-Term Memory (LSTM), a type of network suitable for modeling sequential or time-series data (Hu et al., 2020). In this case, the Tokenizer from the Natural Language Toolkit (NLTK) is used to prepare the text data before it is fed into the LSTM model. The NLTK Tokenizer helps break the text into smaller, meaningful tokens, facilitating the learning and sentiment analysis process. Both approaches can provide deep and accurate insights into user perceptions of library services based on Twitter data.

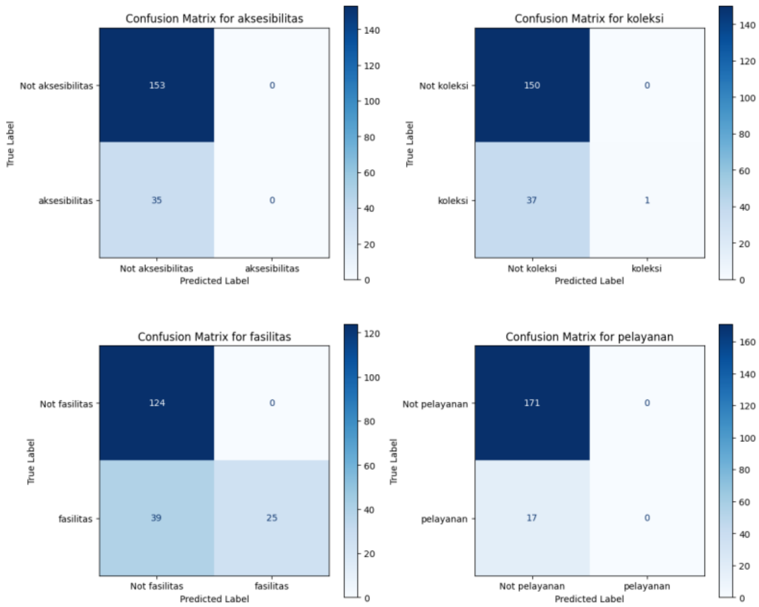

Figure 3. Training model logistic regression TF-IDF

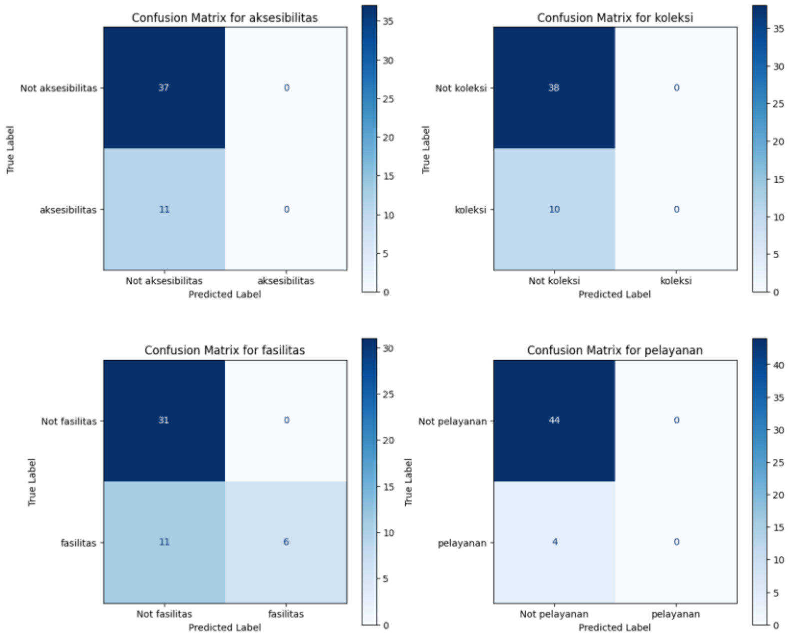

Figure 4. Testing model logistic regression TF-IDF

The confusion matrix results from processing the Logistic Regression model with TF-IDF show that for the categories of accessibility, collection, and service, there are many false negatives, where many data points that should be classified into these aspects are instead predicted as irrelevant. This indicates that Twitter users tend not to highlight these aspects in a positive context. Simply put, Twitter tends to contain more negative complaints than positive appreciative comments.

This finding is supported by previous research. Diyasa et al. (2021) state that Twitter contains more negative complaints than positive expressions of appreciation, with 16.1% of the analyzed tweets being negative. Ruytenbeek et al. (2023) also indicate that Twitter predominantly features negative evaluative language and complaints, such as perceptions of dissatisfaction, impoliteness, and offensive attitudes. In contrast, the category of facilities shows slightly better results with some correct positive predictions. This may indicate that Twitter users more frequently comment on the facilities aspect positively, or that issues related to facilities are more easily recognized by the sentiment analysis model.

Overall, these findings suggest that Twitter users tend to be more critical of aspects such as accessibility, collection, and library services. This could indicate that libraries need to improve the quality of these aspects to meet user expectations. Enhancing accessibility, enriching the collection, and improving service should be key focus areas for library management to boost user satisfaction.

Furthermore, this study demonstrates that Aspect-Based Sentiment Analysis (ABSA) of Twitter data can provide valuable insights into how users evaluate various aspects of library services. By understanding user sentiment towards these specific aspects, libraries can take more targeted actions to enhance their service quality, thereby better meeting user needs and expectations.

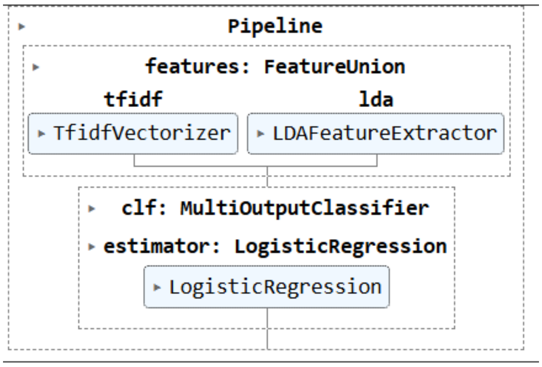

Figure 5. Combination of feature engineering

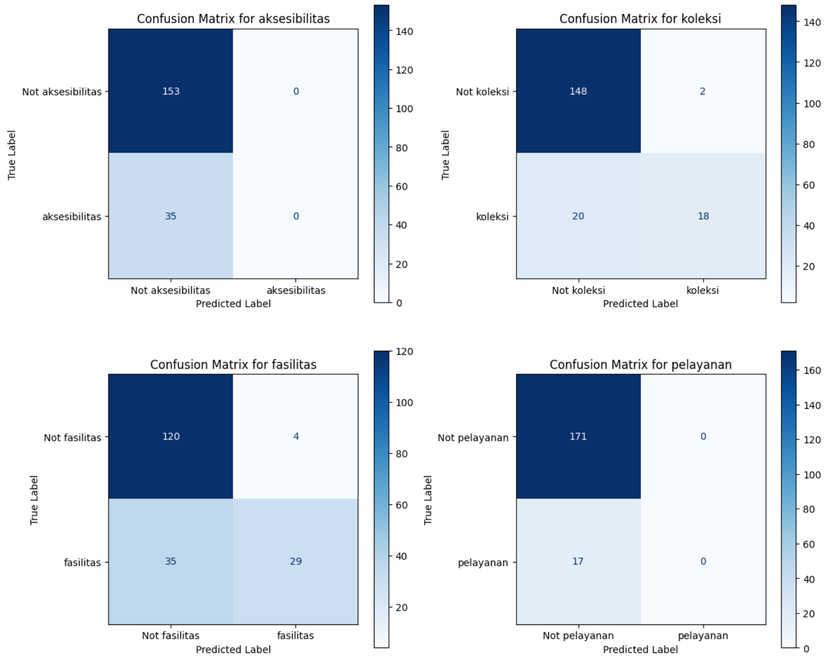

Figure 6. Training model logistic regression TF-IDF + LDA

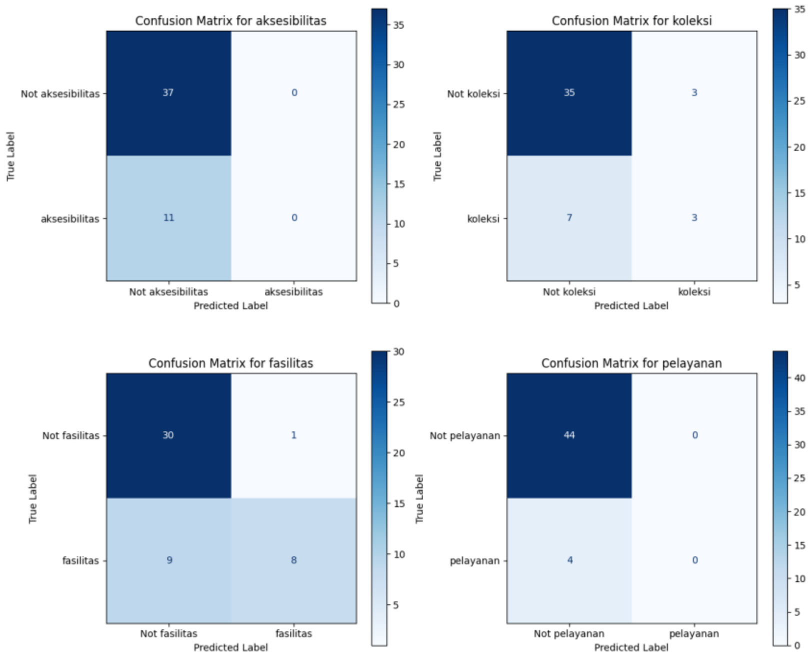

Figure 7. Testing model logistic regression TF-IDF + LDA

The multi-output classification pipeline combines TF-IDF and LDA for feature extraction, followed by Logistic Regression within a MultiOutputClassifier to address multiple sentiment aspects simultaneously. This analysis of Twitter responses provides valuable insights into user perceptions of library service quality.

In the accessibility category, the model shows a lack of positive predictions, indicating that accessibility may be underrepresented or unsatisfactory to users. For collection, some positive predictions were identified, suggesting relatively better attention but still with errors needing improvement. The facilities category received better performance, indicating positive user feedback, though some areas still require improvement. In service, similar to accessibility, there is a lack of positive responses, suggesting enhancements are needed to meet user expectations.

Overall, accessibility and library services emerged as key areas for improvement. Solutions for accessibility could involve integrating digital services, purchasing hardware and software upgrades, and ensuring websites are accessible for all users (Pomputius, 2020; Longmeier & Foster, 2022). For services, optimizing self-service options, enhancing information services, and implementing remote management can improve user satisfaction (Song & Dang, 2022; Obenauf, 2021). Accessibility and service improvements are interconnected, as enhanced accessibility supports better service delivery (Vorontsova & Agibalova, 2021; Shaw & De Sarkar, 2021).

In addition to Logistic Regression, LSTM was applied using the NLTK Tokenizer to enhance sentiment analysis by breaking text into meaningful tokens. This combination of methods allows for a more nuanced understanding of user feedback, guiding future improvements in library services.

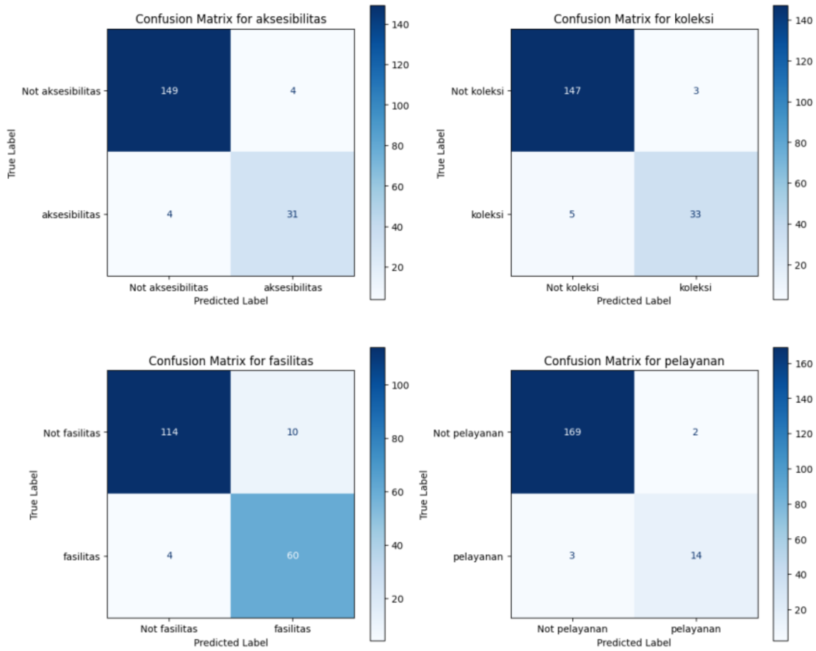

Figure 8. Training odel logistic regression LSTM

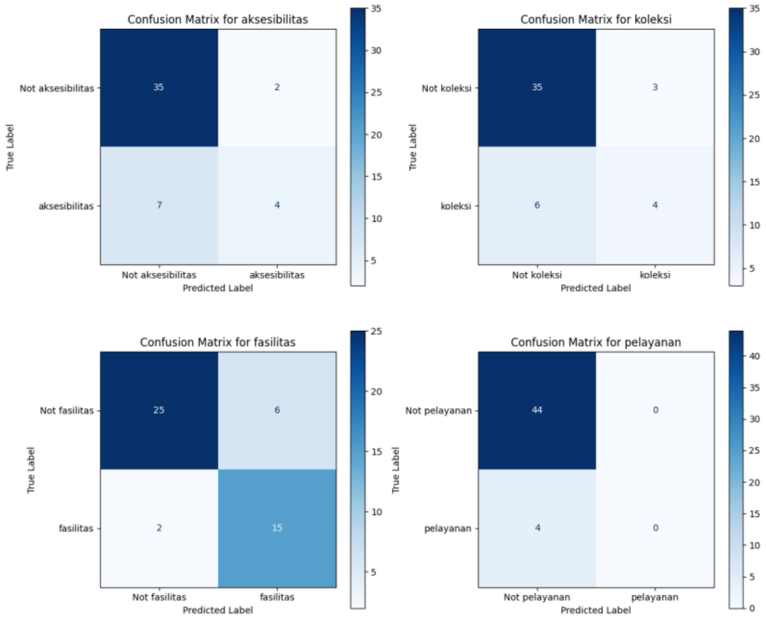

Figure 9. Testing model logistic regression LSTM

The confusion matrix analysis results from the Logistic Regression model with LSTM (NLTK Tokenizer) indicate that the aspects of accessibility and collection received significant attention from Twitter users, with a relatively high number of predictions. This suggests that accessibility and collection are two important aspects frequently discussed by users. Consequently, this implies that libraries need to continuously monitor and improve the quality of these two aspects to meet user expectations.

Regarding the facility aspect, the model shows that, although there were many correct predictions, there are still several errors. This can be interpreted as users having varied opinions about the library's facilities, and there may be dissatisfaction or unmet expectations.

Libraries should focus more on improving and maintaining facilities to ensure user comfort and satisfaction. Research indicates that the availability of service facilities is the most critical factor affecting library users' satisfaction with library spaces, followed by interior design quality, physical environmental elements, spatial diversity, and study space management (Peng et al., 2022).

The service aspect shows significant variation in prediction results. This indicates that service is a crucial area for users and tends to influence their overall perception of the library's quality. Library managers should ensure that library staff are well-trained, friendly, and responsive to user needs (Amarasekara & Marasinghe, 2020) to enhance their experience. Deich (2020) recommends that library staff take the initiative to improve their skills in communication and information technology proficiency.

Overall, findings from this ABSA highlight that aspects of accessibility, collection, facilities, and service have a significant impact on users' perceptions of library service quality. By understanding user sentiment, libraries can take more precise steps toward service improvement and enhancement. This will help libraries meet and even exceed user expectations, ultimately improving the library’s image and value in the community. This study demonstrates that aspect-based sentiment analysis of social media data can be a highly effective tool for evaluating and improving library service quality.

4. CONCLUSION

The research findings indicate that the aspects of Collection and Facilities received the highest levels of positive sentiment, whereas Accessibility and Service were associated with more negative sentiment, signaling key areas requiring improvement. Based on these results, several recommendations can be proposed. For Accessibility, the library could consider extending operational hours and enhancing digital access to better accommodate user needs. Regarding Collection, regular updates and the addition of relevant materials are essential to ensure alignment with current trends and reader interests. In terms of Facilities, ongoing renovation and maintenance are necessary to maintain a comfortable and conducive environment for visitors. Finally, for Service, targeted staff training aimed at improving professional skills and fostering a more welcoming attitude is critical for elevating service quality. Implementing these recommendations is expected to enhance overall user satisfaction and contribute to a more positive and engaging library experience.

AUTHORS’ CONTRIBUTIONS

Evi Fatimatur Rusydiyah: Writing oiginal draft preparation. Ideas; formulation or evolution of overarching research goals and aims. **Prasasti Karunia Farista Ananto:** Ideas; formulation or evolution of overarching research goals and aims.

CONFLICT OF INTERESTS

We state that there are no known conflicts of interest linked with this publication, and that there has been no significant financial assistance for this work that could have influenced its outcome.

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