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# How Stemming Process Ruining the Meaning of Indonesia Phrases and BRL Method as Its Solutions for Handling Complaint Text

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**Abstract**

The stemming process in text preprocessing can ruin the meaning of words in Bahasa Indonesia text mining, potentially influencing the interpretation outcomes or the accuracy of machine learning models when processing complaint texts. Many Indonesians deliver their complaints by text, making this an important issue. Therefore, this research proposes the Be Raw Language (BRL) method for handling complaint texts. BRL generally circumvents several words that, when subjected to stemming, undergo changes in meaning. To ascertain whether a word undergoes changes and as a basis for analysis, this study employs a sentiment analysis approach utilizing 6,205 complaint text data sourced from community reviews concerning tourist destinations. Initially, these reviews are labeled as ground truth, and sentiment calculations are conducted. In the preliminary stage, the research findings indicate an accuracy rate of 60.23%. Subsequently, this study conducts an in-depth analysis on how words in the Indonesian language may change in meaning with the addition of prefixes or suffixes. Consequently, the concept of the BRL method emerges to analyze words without employing stemming and to delineate its approach in interpreting words along with their meanings. The study establishes three main rules for interpreting the meaning of a word or even phrases in Bahasa Indonesia texts to enhance accuracy. As a result, employing the BRL method increases the accuracy rate by 17.57% to 77.80%.

Keywords: Be raw language; skipping stemming in Bahasa Indonesia; Bahasa indoensia text preprocessing; Processing Indonesia complaint text

## 1 Introduction

Understanding complaint text has become the most crucial aspect (Manservisi et al., 2023), (Singh et al., 2021), especially for improving public services that need to be processed quickly (Aditya et al., 2023), (Peng et al., 2022), while the number of complaints is massive (Singh et al., 2021), (Aditya et al., 2023), (Park et al., 2022). Therefore, the need to process the complaint text by machine is important (Chen et al., 2022), (Gupta et al., 2021), because human capability to understand a lot of text in a short time is quite challenging and difficult (Shen & Wang, 2023), (Nundloll et al., 2022). Indeed, the number of complaint texts is a serious issue, for example, in a previous study, there were more than 7.000 tweet from citizens in Indonesia who reported only about traffic and transportation in a city (Lidiawaty et al., 2023a), and another study conducted in another city also reported a huge number of complaints in Indonesia (Madyatmadja et al., 2022).

The initial problem is that the Bahasa Indonesia language is difficult to learn (Lutfiana, 2021), (Haiyudi & Art-In, 2021). Many prior studies have focused on developing a model for sentiment analysis (Kusumaningrum et al., 2023), (Gozal et al., 2023), classification (Amalia et al., 2020), or clustering (Daneshfar et al., 2024), (Ma & Zhuge, 2024). Lack studies focused on how to interpreted the Bahasa Indonesia text, If there is any, it is focused on the calculation of word vectors approach (Lidiawaty et al., 2023a), (Muftie &

Haris, 2023), (Kusumawardani et al., 2018). However, knowing the context and obtaining information from the text are important for natural language processing (Yang et al., 2021), Considering that certain words lose the meaning during natural language processing (El-Alami et al., 2022). Moreover, in the objective of handling complaint text, it can suggest steps that can be taken based on these complaints (Singh et al., 2021), (Ibrahim & Wang, 2019), (Ding et al., 2024), (Lidiawaty et al., 2023).

Interpreting complaint texts becomes urgent (Wang & Zhong, 2020), given the abundance of such texts requiring interpretation as the basis for decision-making for handling it (Peng et al., 2022), (Chen et al., 2022). Certainly, in text interpretation, it is imperative to discern the actual meaning of the text (El-Alami et al., 2022), in addition to understanding the sentiment conveyed through opinions expressed in the complaint text. Although several sentiment analysis studies have been conducted to understand the emotional nuances of a text based on the polarity value of words (Tho et al., 2021), (Kusumawardani & Maulidani, 2020), this research reveals that certain words in Bahasa Indonesia experience a shift in meaning through the addition of prefixes or suffixes (Yosephine & Prabowo, 2017), (Natalia & Wulandari, 2017). This causes these words to change their meanings during the stemming process (Lidiawaty et al., 2023a), (Lidiawaty et al., 2022). On the other hand, stemming processes are important for preprocessing the text stage to avoid misunderstanding the same meaning word with a different form of word (Adriani et al., 2005), (Chung, 1976). A prior study has used the n-gram method to understand the phrase from Bahasa Indonesia text; however, the result still shows that there is no evidence of a significant result (Ibrohim & Budi, 2019), (Ibrohim & Budi, 2023). Therefore, this study focuses on mitigating this phenomenon with two following research questions; The first research question is; how does the pattern of word switching mean in the stemming process in Bahasa Indonesia? Moreover, the second research question is; what is the approach to avoid a shift in meaning in text preprocessing in Bahasa Indonesia?

The main objective of this study is to analyze the pattern when words shift meaning in the stemming process and propose a method approach to its problem. Therefore, the first step is to list the words that shift or change meaning after the stemming process. The approach employed in this study involves utilizing lists of positive and negative words that are typically used in sentiment analysis. The most appropriate approach undertaken in this research was to compare the sentiment outcomes of words before and after stemming. This logic is simple, yet comprehensive, and plausible. If sentiment is shifting, so does the meaning.

This study also addresses the issue of semantic bias resulting from stemming processes by proposing the Be Raw Language (BRL) method as a solution. Instead of overlooking stemming entirely, the BRL model incorporates a selective stemming approach, filtering out specific words that are deemed inappropriate for stemming. These words are gathered from several terms that exhibit negative polarity but acquire positive polarity values after undergoing the stemming process (and vice versa). The approach, though relatively simple, proves to be optimal in deciphering the semantic nuances of phrases. Be Raw Language adopts an unconventional method that abstains from preprocessing words, preserving their 'raw' or original form rather than transforming it to root words. This method is particularly advantageous for text processing, particularly in contexts involving complaints.

## 2 Heading and Section

In general, before demonstrating how the Be Raw Language (BRL) method operates, this chapter also provides a detailed explanation of the stages conducted in this research. The whole stages is illustrated in Figure 1. Started from collecting the text data, labelling the collected complaint text, check the sentiment using BRL method and verify each word for discrepancies in accuracy.

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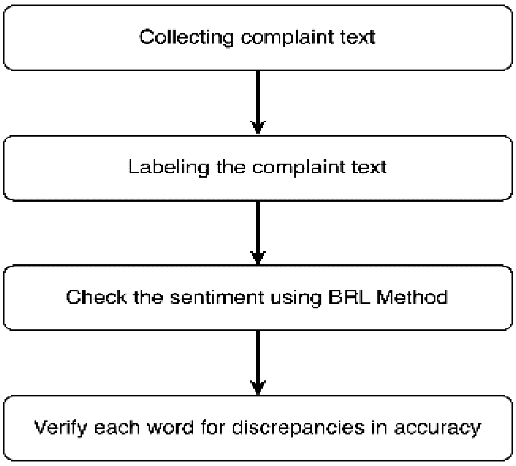


Figure 1. General methodology

*A. Collecting Complaint Text*

This study utilized complaint text data to attain an in-depth analysis of the utilization of the Indonesian language by the public in composing complaint texts. Based on observations from previous research, individuals tend to employ suggestive language when submitting complaints (Lidiawaty et al., 2024). The use of suggestive language renders Indonesians more challenging to analyze, as it tends to employ polite expressions when criticizing compared to direct expressions of anger.

Table 1. Data samples

| **Review** | **Rating** | **Date** | **Real_label** | **Sys_Label** | **Accuracy** |
|---|---|---|---|---|---|
| Fasilitas bisa ditingkatkan, speaker dan semprot pemadam kebakaran tidak memadai.. protokol emergency jg bisa dibuat mengingat 2x kejadian kebakaran selama 2022. | 1 | 1661336592 | negative | negative | TN |
| Mainan2 playground prlu diremajakan. Masa anak pertama main tahun 2012 masih ada dan diperbaiki asal2an. Membahayakan byk karat | 2 | 1672821495 | negative | negative | TN |
| Standar banget. Cuma lasih kerjaan satpol PP doank. Kurang HUMANIS utk para pengunjung. Beda banget sama jaman bu risma | 2 | 1669710023 | negative | negative | TN |
| Museumnya kecil, ga seberapa besar. Kalau mau kesini, harus reservasi tiket secara online dulu karena ada pembatasan pengunjung. Tiketnya gratis kok. Batas waktu di dalam museumnya 30 menit. Pegawainya ramah, tempatnya bersih, toilet bersih, mushola juga nyaman, ruangan museumnya ber AC, disekitarnya banyak tumbuhan hijau-hijau taman gitu. Disini juga cocok untuk pembelajaran anak-anak kecil soal pendidikan di indonesia jaman dulu. Parkiran kendaraan ada di sebelum museumnya yaa... | 5 | 1641126948 | positive | positive | TP |
| Sayang klau masuk kampung ini sepeda ngk boleh dinaiki padahal ggnya panjang2, jadi sebagai driver online kurang suka klau dpt orderan dikampung ini???? | 3 | 1633501210 | neutral | positive | FP |
| Sebenarnya yang cocok itu daerah Peneleh,Ampel, bukanny Maspati | 1 | 1622184671 | negative | positive | FP |

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| Review | Rating | Date | Real_label | Sys_Label | Accuracy |
|---|---|---|---|---|---|
| Jangan lupa pesan tiket secara online dulu di tiketwisata.surabaya.go.id ya teman-teman, meskipun waktu ke sana sepertinya masalah per-tiket-an ini cukup longgar, sudah ga se-strict waktu awal pandemi. Salah satu museum dengan interior yang instagramable, agak berbeda dari yang lain, terutama penggunaan materialnya. | 4 | 1653827201 | positive | negative | FN |

Therefore, this research focuses on gathering complaint texts submitted by the public in a specific sector, aiming to address the first research question, which is to identify patterns of words undergoing shifts in meaning, serving as the foundation for developing the BRL method.

The complaint text obtained from visitors who filled out reviews on the Google Maps section. The management of this text complaint is important, because it contains words that must be interpreted as a unit to understand their meaning or sarcasm (the text seems polite, but the actual meaning is not). Each word must be understood in its context along with the preceding word, so that the overall meaning can be maintained. To collect text complaint data, a scraping technique using the Google Maps API was used. As a result, 6205 text complaint data points were successfully collected for analysis. The sample complaint text data can be seen in Table 1.

There are six important attributes in the data used in this study, as listed in Table 1. These attributes include review, rating, date, user name, real_label, sys _label, and accuracy. The "Review" attribute represents complaint text collected from Google reviews, the type of the data is string. The "Rating" attribute indicates the number of stars given by visitors in Google Map. The "Date" attribute records the date when the complaint was written, it saved in Unix timestamp. Unix timestamp is a system for tracking time, which is represented as the number of seconds elapsed since the Unix epoch. For example, in the first data, the date "1661336592" indicated that the visitor sent their complaint in August 24, 2022 at 10:23:12. The "real_label" attribute is labeled as the ground truth. The "sys_label" attribute is a label that the calssification result using BRL method. The "Accuracy" attribute reflects the level of accuracy between real_label and sys_label. The accuracy values obtained by matrix confusion are listed in Table 2.

Table 2. Matrix confussion used in this study

| Real_sentiment | Sys_sentiment | | |
|---|---|---|---|
| | Positive | Negative | Neutral |
| **Positive** | TP | FN | FNet |
| **Negative** | FP | TN | FNet |
| **Neutral** | FP | FN | TNet |

Based on Table 2, there are six possible values for the accuracy attribute. True Positive (TP) appears when sys_sentiment and real_sentiment both classify the complaint text as positive. The value of a False Positive (FP) appears when real_sentiment is classified as positive, but real sentiment does not. True Negative (TN) is the condition when sys_sentiment classifies the complaint text as negative, as does real_sentiment. On the other hand, when sys_sentiment is classified as negative but real_sentiment is not, the value of the accuracy becomes False Negative (FN). True neutral (TNet) indicates that both real_sentiment and sys_sentiment classify the text as neutral sentiment, meaning that if the sys_sentiment is classified as neutral but the real sentimen does not, the value of the accuracy will be False Neutral (FNet).

*B. Labelling the complaint text*

The sentiment analysis labeling process in this study consists of two methodological stages aimed at determining the real_sentiment value. Initially, the real_sentiment attribute value is filled with ratings provided by visitors. Ratings of 1 or 2 are interpreted as negative, 3 as neutral, and 4 or 5 as positive. However, prior research has found that ratings may sometimes not align with the textual content (Ghasemaghaei et al., 2018). Therefore, this study necessitates a second method to determine the value for the real_sentiment attribute. When the accuracy between

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real_sentiment and sys_sentiment still differs during this process, a lexicon-based labeling process is employed. The lexicon approach is chosen because lexicons contain sentiment definitions for individual words (Huang et al., 2022), thus rendering the labeling process efficient (Catelli et al., 2023), (Wu et al., 2024).

*C. Check the sentiment using BRL method*

As proposed, sentiment checking is conducted as a basis for determining semantic changes or lack thereof. Thus, in the development of the BRL method, additional processes are incorporated, as depicted in the blue block in Fig 2.

Fundamentally, the approach used in this study was based on the basic sentiment analysis method. It is initialized with the complaint texts as input, and then the text preprocessing phase. The text preprocessing phase includes case folding, stopword and punctuation removal, stemming, and tokenization. The next step involves comparing each tokenized word with positive and negative corpora. Furthermore, according to the BRL approach, it is necessary to compute the total count of positive and negative words, culminating in the computation of sentiment scores. The straightforward approach using the BRL method dictates that if the count of positive words exceeds that of negative words in a given complaint text, the system classifies the text as positive. Conversely, if the count of negative words outweighs that of positive words, the system classifies the complaint text as negative. However, if the counts of positive and negative words are equal, the system that employs the BRL method classifies the text as negative.

The BRL method provides a bypass for certain words to avoid stemming, therefore it has a different process after text preprocessing and before calculating the counts of positive and negative words. The BRL method excludes a set of words from stemming, and in the next step, determines whether these words have positive or negative sentiments (depicted by two blue blocks in Figure 2. Then, the counts of positive and negative values are computed along with other words that undergo stemming as normal steps (depicted by the black flow in Figure 2).

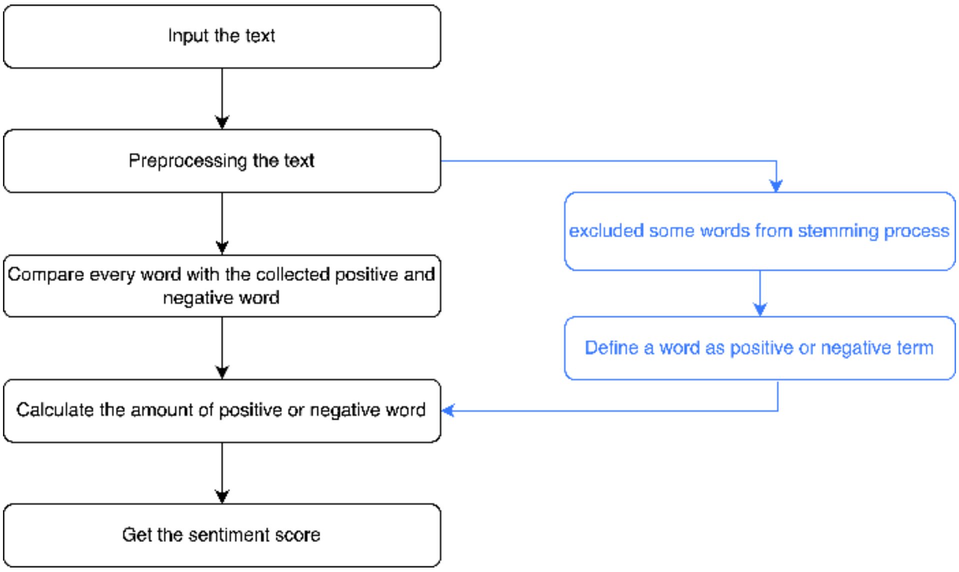


Figure 2. Verify each word for discrepancies in accuracy

*D. Check the sentiment using BRL method*

In general, the accuracy calculation process uses (1) computes the values of TP, TN, TNet, FP, FN, and FNet obtained from Table 2. The sum of the true values is divided by all the data (n) to obtain the accuracy value (a).

$$a = \frac{(TP + TN + TNet)}{\sum n} \tag{1}$$

In this study, three accuracy calculation processes were used. The first accuracy value was computed after the first labeling process, and the second accuracy value was calculated after the

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second labeling process. The initial BRL method was applied in the second-accuracy calculation process. However, during this process, it also identifies the words exempted from stemming. The full application of bypassing words without the need for stemming occurs in the third accuracy calculation process, which utilizes the rules obtained from the BRL method. For more comprehensive results, please refer to Table 4.

## 3 Results and Discussions

This chapter will elucidate the findings obtained from this research. It will commence with an explanation of the patterns identified to determine raw words for conversion into raw language, followed by a discussion of accuracy values. Additionally, it will expound on how the BRL method operates in general and highlight the challenges and limitations encountered in this study, serving as a foundation for future research.

### *A. The raw words*

As explained in the previous chapter, the Be Raw Language (BRL) method bypasses several words to avoid stemming, without omitting the stemming process itself. It is well-known that stemming is necessary to gather information on words that have the same meaning but different affixes. However, the issue encountered is that some words, after undergoing affixation, alter the meaning of the word and even change its sentiment value. Examples of such words can be seen in Table 3.

Based on Table 3, concluded that several words have different meanings compared to their base forms, particularly in the context of complaints. Out of the 8 words initially belonging to the group of base adjectives with negative sentiment, their sentiment turns negative after acquiring the prefixes me(mper)+ or di(per)+. Furthermore, the majority of them have suffixes such as +an or +i. For instance, the base word "lengkap" with the meaning "complete" changes its meaning to a request for completion after receiving the prefixes di+lengkap+i. There is no difference in meaning between the prefixes di+ and me+, as the prefix me+ merely indicates active voice, while the prefix di+ indicates passive voice in a verb. From Table 3, it can also be inferred that the significant influence occurs when there is a change from the base word after affixation, turning the word into a verb, even though the base word is not a verb.

Table 3. Examples of word that change meaning after the stemming process

| Word without stemming | Form | Meaning | Sentiment | Word after stemming | Form | Meaning | Sentiment |
|---|---|---|---|---|---|---|---|
| diperbaiki/ perbaiki | verb | (please) fix it (!) --> the inclination to request an improvement | negative | baik | adjective | good | positive |
| sebaiknya | adverb | should be --> The opening statement to express suggestions, because something is not proper | negative | baik | adjective | good | positive |
| perbaikan | verb | refinement | negative | baik | adjective | good | positive |
| diperbanyak/ perbanyak/ memperbanyak | verb | (please) add more (!) --> indicates that the available facility is currently not enough | negative | banyak | adjective | many / much | positive |
| ditingkatkan/ tingkatkan/ meningkatkan | verb | (please) upgrade/ improve --> the request for upgrading (one/some facility-es) | negative | tingkat | noun | upgrade | neutral |
| dibenahi | verb | (please) fix it (!) --> the inclination to request an improvement | negative | benah | precategorical or noun | **to tidy up** (verb) **part of land/kind of bug** (noun) | neutral |

| Word without stemming | Form | Meaning | Sentiment | Word after stemming | Form | Meaning | Sentiment |
|---|---|---|---|---|---|---|---|
| diperhatikan/ memperhatikan | verb | be aware of --> indicates that something left improperly | negative | hati | noun | **heart** (methaphor, e.g. the sound of the heart. **liver (**literal meaning) | neutral |
| dilengkapi/ melengkapi | verb | (please) fulfill --> indicates something is unavailable | negative | lengkap | adjective | complete | positive |
| diperluas/memperluas | verb | (please) expand | negative | luas | adjective | large | positive |
| disegerakan/ menyegerakan | verb | as soon as possible | negative | segera | adverb | soon | positive |
| disediakan/ menyediakan | verb | (please) provide --> indicates that something is not provided yet | negative | sedia | adjective | available | positive |
| dikembangkan/ mengembangkan | verb | expand --> indicates that one or more facilities is not enough yet | negative | bentang | verb<br>noun | open (verb)<br>flower (noun) | positive |
| dijelaskan/ menjelaskan | verb | explain --> indicates something unclear | negative | jelas | adjective | clear | positive |
| diperbaiki/ perbaiki | verb | (please) fix it (1) --> the inclination to request an improvement | negative | baik | adjective | good | positive |
| sebaiknya | adverb | should be --> express suggestions, because something is not proper | negative | baik | adjective | good | positive |

$$mem(mper) + root\ word + i\ (or)\ kan \tag{2}$$
$$di(per) + root\ word + i\ (or) kan \tag{3}$$

In general, a rule is established that base words receiving the prefixes di(per)+ or me(mper)+ and undergoing a change in their word form to become verbs are formulated as words that do not require stemming. However, in practice, there are specific cases. For example, the word "baik" (good), which is an adjective, receives the prefixes se+baik and the suffix baik+nya, forming an adverbial group. Nevertheless, its sentiment still changes from "baik" (positive sentiment) to "sebaiknya" (negative sentiment), indicating a request for improvement by the sender. However, in this study, the rule is still applied that when a word receives the prefixes di(per)+ and the suffix +i or +kan and undergoes a change in its word form to become a verb, the word is indicated as a set of words that do not require stemming and are left be raw form, as seen in (2) and (3).

There is no different meaning between words receiving affixes as outlined in (2) and (3). The difference lies only in active and passive voice structures. The (2) indicates verbs used in active sentences, while (3) indicates passive sentences. However, in terms of literal meaning, there is no difference between them. This result lead for a new assumption rule in developing BRL method the it is necessary to not stem the word(s) from (2) and (3) and make the sentiment as negative.

*B. The comparison of the accuracy*

After understanding the formulation and workings of BRL, this section will elucidate the accuracy obtained from several experiments. Generally, these results are presented in Table 4. In Table 4, there are several schemes for calculating accuracy. The first scheme is the first label scheme, where the accuracy of BRL's operation is calculated using ground truth labels derived from rating rules as explained in Chapter 2C. Subsequently, for reviews where the accuracy in the confusion matrix is still not TP, TN, or TNet, we used lexicon for labeling the reviews or the complaint text. In the last scheme or when the BRL Method applied, the system starts allowing stemming for some words that change their

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meaning after receiving affixes, as detailed in the subsequent subsection.

The rating cannot be directly used as a reference for assigning sentiment labels. As evidenced in Table 4, the matrix of accuracy value between the original label and the label from the system that has not implemented BRL obtained an accuracy value of 57.15. Subsequently, a second scheme experiment was conducted, where each accuracy result obtained from scheme 1 that was still False Positive (FP), False Negative (FN), or False Neutral (FNet), was relabeled using a lexicon. As a result, the accuracy value increased by 3.08% to 60.23%. Next, the third scheme involves calculating accuracy entirely using the "BRL Method." This is referred to as entirely using the "BRL Method" because, in this scheme, several words have already been filtered out to avoid stemming. The results showed a significant increase of 17.57% to 77.80%.

Table 4. The comparison of the accuracy

| Matrix of accuracy | The scheme | | |
|---|---|---|---|
| | First label | Second label | BRL method |
| **TP** | 3182 | 3349 | 3153 |
| **TN** | 231 | 258 | 250 |
| **FP** | 565 | 567 | 548 |
| **FN** | 749 | 563 | 771 |
| **Tnet** | 134 | 131 | 136 |
| **Fnet** | 1345 | 1338 | 1348 |
| **Accuracy** | 57.15% | 60.23% | 77.80% |

*C. The explanation of how BRL method works*

In this sub-section, a detailed explanation of how the BRL method works and the rules that need to be observed will be provided. Based on Table 3, a rule is established that stemming is not necessary for words that fall under the characteristics (2) and (3). Furthermore, this section will explain how other rules are derived from the analysis of several experiments.

**Assumption Rule 1:** Do not stem the word(s) from (2) and (3) and let them as the 'raw' word. Then, make the sentiment word as negative.

After identifying the words that are left 'raw' and not subjected to stemming in Assumption Rule 1, this chapter will explain how the BRL method works on a complaint. In Table 1 related to the sample data, it will be explained in this chapter how review number 1 is considered TN, how review number 4 is considered TP, how review number 6 is considered FP, and how review number 7 is considered FN. For each of these review examples, the calculations will be explained using the BRL method approach.

In review 1, the label used as the "real_sentiment" indicates a negative sentiment analysis. Furthermore, it will be explained why the sentiment by the BRL method or on the attribute "sys_sentiment" also provides a negative sentiment analysis value. Review 1 is written as "Fasilitas bisa ditingkatkan, speaker dan semprot pemadam kebakaran tidak memadai. protokol emergency jg bisa dibuat mengingat 2x kejadian kebakaran selama 2022.", which means "Facilities can be increased, speakers and fire extinguishers are inadequate. Emergency protocols can also be made considering 2 times the incidence of conflict for 2022." After preprocessing, this sentence becomes "fasilitas ditingkatkan speaker semprot madam bakar pada protokol emergency jg 2x jadi bakar 2022".

Table 5. The sentiment calculation of Review 1

| Moethod | The reviews | p | n | result |
|---|---|---|---|---|
| Without BRL method | fasilitas **tingkat** (p) speaker semprot madam bakar pada protokol emergency jg 2x jadi bakar 2022 | 1 | 0 | positive |
| With BRL method | fasilitas **ditingkatkan** (n) speaker semprot madam bakar pada protokol emergency jg 2x jadi bakar 2022 | 0 | 1 | negative |

As known, there is a word process that is not stemmed, namely the word "*ditingkatkan*" or [(please be) increased], which is not stemmed. Meanwhile, the word "*pemadam*" or "extinguisher" is stemmed to the word "*padam*" or "*off*". This indicates that in this process, there has been a filtering process for words that are not stemmed. As known, the word "ditingkatkan" has a negative sentiment because it implies existing facilities needing to be increased; if stemmed, it would become "tingkat", which means "level (up)" and

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has a positive sentiment. Furthermore, after the review has undergone preprocessing, the calculation of its positive and negative values can be seen in Table 5. The attribute **p** in Table 5 – Table 8 indicates the number of positive word count, and the attribute **n** indicates the number of negative word count. In attribute 'The reviews', if after word there is a blue code as p, it will add the value of p attribute. Moreover, if after the word there is a red code as n, it will add the value of n attribute. The result will be positive if the p value is higher than the n value, otherwise the result will be negative. However, if the p and n have the same value, the result will be neutral.

The expected sentiment result from Review 1 in Table 5 is expected to be negative as indicated by the Real_label value in Table 1. By using the BRL method (Assumption Rule 1), it is proven to produce the correct sentiment value compared to not using the BRL method. According to Assumption Rule 1, the word "ditingkatkan" is not stemmed, and the sentiment value automatically becomes negative.

Table 6. The sentiment calculation of Review 4

| Moethod | The reviews | p | n | result |
|---|---|---|---|---|
| Without BRL method | museum **besar** (p) kesini reservasi tiket online batas unjung tiket **gratis** (p) batas museum 30 menit pegawai **ramah** (p) tempat **bersih** (p) toilet **bersih** (p) mushola **nyaman** (p) ruang museum ber ac sekitar tumbuh hijau hijau taman gitu **cocok** (p) pembelajaran anakanak didik indonesia jaman parkir kendara museum yaa | 7 | 0 | positive |
| With BRL method | museum **ga besar** (n) kesini reservasi tiket online batas unjung tiket **gratis** (p) batas museum 30 menit pegawai **ramah** (p) tempat **bersih** (p) toilet **bersih** (p) mushola **nyaman** (p) ruang museum ber ac sekitar tumbuh hijau hijau taman gitu **cocok** (p) pembelajaran anakanak didik indonesia jaman parkir kendara museum yaa | 6 | 1 | positive |

Next, it will be explained in Table 6 how the BRL method assigns a positive value to a review. Without using the BRL method, the p value is actually higher (with 7 words) and no negative words are found. However, after using the BRL method, 1 n value appears. This n value is derived from the researcher's hypothesis that any word following "ga/nggak/enggak/bukan/tidak," which means "not," will have a negative sentiment. This also explains why the words ga, nggak, enggak, bukan, and tidak are not removed during the stopword removal process.

In Table 6 shows the BRL method assigns a positive value to a review. Without using the BRL method, the p value is actually higher (with 7 words) and no negative words are found. However, after using the BRL method, 1 n value appears. This n value is derived from the researcher's hypothesis that any word following "ga/nggak/enggak/bukan/tidak," which means "not," will have a negative sentiment. This also explains why the words ga, nggak, enggak, bukan, and tidak are not removed during the stopword removal process.

**Assumption Rule 2**: If the words "ga," "nggak," "enggak," "bukan," or "tidak" appear, then ignore the following word and change the sentiment to negative.

Table 7. The sentiment calculation of Review 6

| Moethod | The reviews | p | n | result |
|---|---|---|---|---|
| Without BRL method | **benar** (p) **cocok** (p) daerah penelehampel **bukan** (n) maspati | 2 | 1 | positive |
| With BRL method | **benar** (p) **cocok** (p) daerah penelehampel **bukan** maspati (n) | 2 | 1 | positive |
| Improvement | **sebenarnya (n)** **cocok** (p) daerah penelehampel **bukan maspati (n)** | 1 | 2 | negative |

Imagine if there is a phrase "nggak bersih" or "not clean." Without Assumption Rule 2, the BRL method would define its sentiment as neutral. This is because the word "nggak" or "not" has a negative value (n), while the word "bersih" or "clean" has a positive value (p). According to the BRL method,

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if the p and n values are balanced, the review is given a neutral sentiment. However, the phrase "not clean" has a negative sentiment. Therefore, by following Assumption Rule 2, the phrase "nggak bersih" will automatically be considered to have a negative sentiment value.

Table 8. The sentiment calculation of Review 7

| Moethod | The reviews | p | n | result |
|---|---|---|---|---|
| Without BRL method | lupa pesan tiket online tiketwisatasurabaya go id ya temanteman tiket **longgar** (p) ga sestrict pandemi **salah** (n) museum interior instagramable beda guna material | 1 | 1 | neutral |
| With BRL method | lupa pesan tiket online tiketwisatasurabaya go id ya temanteman tiket **longgar** (p) **ga sestrict** (n) pandemi **salah** (n) museum interior instagramable beda guna material | 1 | 2 | negative |
| Improvement | lupa pesan tiket online tiketwisatasurabaya go id ya temanteman tiket **longgar** (p) **ga sestrict** (p) pandemi **salah** (n) museum interior instagramable beda guna material | 2 | 1 | positive |

Moreover, an analysis will be conducted regarding how the BRL method still makes errors in classifying classes like in Tables 7 and 8. In Table 7, which discusses the result of Review 6 in Table 1, the real_sentiment shows a negative sentiment value. However, the system indicates a positive sentiment value, even though the BRL method has been applied. The issue lies with the word "sebenarnya," which literally translates to "actually," but in the context of complaints, it is more interpreted as "suppose to," indicating a previous condition lacking. Therefore, words with affixes other than those in equations 1 and 2 need to be identified to be classified as words that do not require stemming and are interpreted as negative sentiment.

**Assumption Rule 3**: It is necessary to identify words that can change sentiment other than the words formulated in Assumption Rule 1.

Meanwhile, in Table 8, the accuracy result for review 7 is FN, where the real_sentiment provides a positive label, while the system with the BRL method classifies its sentiment as negative. The issue with review 7 lies in the rule formulated earlier, namely rule 2. In Table 8, it can be observed that there is the phrase "ga sestrict," consisting of the words "ga" and "sestrict." Following rule 2, any word following the word "ga" will be classified as having a negative sentiment value. However, in this case, "ga sestrict" means "not that strict," indicating that some rule in that place is not that strict so people can enjoy the place. From this finding, it needs an improvement in Assumption Rule 2: If the words "ga," "nggak," "enggak," "bukan," or "tidak" appear, then the sentiment value is the opposite of the following word. Therefore, these are three rules found in developing and implementating the BRL method:

**Rule 1:** Do not stem the word(s) from (2) and (3) and let them as the 'raw' word. Then, make the sentiment word as negative.

**Rule 2:** If the words "ga," "nggak," "enggak," "bukan," or "tidak" appear, then the sentiment value is the opposite of the following word.

**Rule 3**: It is necessary to identify words that can change sentiment other than the words formulated in Assumption Rule 1.

When encountering the presence of the terms "ga," "nggak," "enggak," "bukan," or "tidak" followed by an adjective within a phrase, the resultant sentiment value is inverted in relation to the sentiment conveyed by the adjective. For instance, if the phrase "tidak cantik" or "not beautiful" is encountered, it signifies the opposite meaning, suggesting "ugly" or negative sentiment. Hence, when such adjectives as "cantik" or "beautiful" inherently carry positive sentiment, their occurrence following the aforementioned terms implies a connotation of "not beautiful," thereby implying a negative sentiment, or in essence, "ugly."

### *D. Challenges and limitations*

Indonesian is used by over two hundred million people in Indonesia, where it functions as the national language and is extensively used in public services. In today's era of automation, the processing of the Indonesian language is becoming increasingly vital, especially in handling complaints submitted by the community through reviews, social media, and other channels. Therefore, this research aims to comprehensively understand the characteristics of society when submitting their complaint texts. Several findings and rules have been detailed in the preceding sub-sections. However, various challenges and issues persist, particularly in optimizing the performance of the BRL method.

Beyond the inherent complexities of the Indonesian language, additional issues arise in processing Indonesian texts that contain shortened words. This is especially prevalent when sourcing data from social media, where users often abbreviate words for brevity while maintaining comprehensibility. Nonetheless, this poses a distinct challenge in machine training.

## 4 Conclusions

This study aims to develop a BRL model that attempts to overcome the problem of word meaning shifting after the stemming process. The approach used when developing the BRL method is to examine the sentiment results of a word before and after stemming. From this process, a word structure pattern was obtained, which is recommended not to be stemmed in the Bahasa Indonesia text mining process because it has the potential to change the meaning of a word, especially in the complaint text domain. In general, the results show that verbs that are given affixes, whether prefixes or suffixes, lead to changes in the sentiment context. In Bahasa Indonesia, a change in sentiment indicates a change in meaning. Especially in the case of complaint texts, words that indicate negative sentiments indicate disappointment or hope that must be captured by the service owner. Therefore, in the BRL method approach, extracting verbs that are given these affixes is not set and leaves the word as it is. In addition, in the second rule, the BRL method also pays attention to Indonesian phrases where the word meaning "not" followed by positive adjectives will produce negative sentiment, so the BRL method bypasses any words after the word meaning "not" which will automatically be interpreted negatively. The final finding, apart from verbs that are given affixes that can change meaning, several other words need to be studied further in future research to perfect the BRL method. In general, the BRL method can increase the accuracy of sentiment analysis from 60.23% without the BRL method to 77.8% after implementing the BRL method.

## 5 Future Work

In this study, the words falling under Rule 1 are still organized into a one-dimensional list. Consequently, during the stemming process, it is only necessary to determine whether a word belongs to this list. If it does, stemming is deemed unnecessary for that word. In future research, a formulation will be tested to optimize the BRL method, enabling it to recognize the types of words specified in Rule 1. Moreover, it is essential to evaluate the speed and accuracy of this development. Additionally, to address the challenges posed by abbreviated words and mixed languages, the implementation of an online KBBI library, or the Indonesian dictionary library, will be tested to tackle these issues.

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