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Constructing and Analysing the MalaySarc Dataset: A Resource for Detecting and Understanding Sarcasm in Malay Language

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Abstract **-** Social media platforms provide users with an efficient and effective way to interact with content without requiring lengthy or complex textual expressions. However, sarcasm in social media discourse has become a serious problem for researchers. Compared to English and several other main languages, the research on sarcasm and the accessibility of reference materials in the Malay language are still significantly lagging. Therefore, this study aims to develop a new dataset of Malay sarcasm detection by detailing each process step, from data collection to filtering to annotation. The dataset consists of two types of data: Facebook comments and its emotion reaction buttons, which include 6,325 non-sarcastic texts and 1,380 sarcastic texts. In addition, the descriptive analysis of this dataset was also conducted to determine the usage patterns of the main features of Malay sarcasm. The analysis shows that emoji is one of the features that play an essential role in determining sarcastic comments. Besides, there are pattern-based features based on the identification of high-frequency terms in the text. The resulting dataset provides diverse examples of sarcasm that consider the linguistic and cultural nuances of the language, thus improving the accuracy and reliability of identifying social media. The findings will aid future research in developing automatic Malay sarcasm detection models using machine learning.

***Keywords*:** sarcasm dataset, sarcasm detection, Malay sarcasm, sentiment analysis, social media

1. Introduction

Social media has become the go-to platform for discussing controversial topics, with sentiment analysis being a popular method for measuring the overall sentiment towards a subject. The sentiment of a topic can be measured based on the comments and responses made. Such analyses help government and private organizations make informed decisions. However, the accuracy of these analyses can be challenged by the presence of sarcasm features in comments. Sarcasm is a form of sentiment where the expressed sentiment is the opposite of what is actually meant, making it challenging to accurately analyse the sentiment of a text. While researchers have extensively covered sarcasm in sentiment analysis for the English language, other languages, including Malay, require more attention. The lack of reference sources in the Malay language has led to the need for creating more public datasets on sarcasm, as it can help researchers conduct more profound analyses of this subject. Besides, Eke et al. [1] highlighted the lack of publicly available annotated datasets in this research domain and stressed the need for standard public datasets for classification experiments on sarcasm identification. Therefore, this study aims to fill this gap by developing a standard public dataset of Malay sarcasm detection.

In addition, the selection of sarcasm features also plays an important role in identifying sarcasm. Sarcasm is a complex linguistic phenomenon involving language's use to convey the opposite of its literal meaning [2]. It can be influenced by several factors, including the speaker's intention, the context of the message, and the audience. For instance, sarcasm can be used to express humour, criticism, or irony, depending on the speaker's intention and the context of the message. Moreover, the use of sarcasm can vary significantly across different social contexts and cultures. What may be considered sarcastic in one culture or social context may not be same as in another.

Therefore, when building a sarcasm detection model, it is essential to carefully select the relevant features that can help accurately identify sarcasm in a given context. These sarcasm detection features may include linguistic cues, such as lexical, pragmatic, hyperbole, pattern-based, syntactic, and metaphoric, as well as contextual factors, such as the speaker's tone, the audience, and the social and cultural context. Besides, different social media platforms may have unique communication norms and practices that can influence sarcasm based on click-based features, such as Facebook emotion reaction button, like button, and rating star [3]. By selecting the right features, a sarcasm detection model can improve its accuracy and generalizability across different contexts and cultures. Our contribution to this paper can be summarized as follows:

- we show process of collecting data from social media and data annotation for sarcasm dataset;
- we introduce new Malay social media sarcasm dataset, which consists of two types of data; Facebook comments and its emotion reactions; and
- we analyze the pattern of sarcasm features usage in the Malay text dataset.

The rest of this paper is organized as follows. In Section 2, we briefly review the existing sarcasm dataset and related work. The methodology used to create the Malay sarcasm dataset and workflow for annotation process are presented in Section 3. Section 4 presents the descriptive analysis of the constructed dataset. Finally, we summarize the conclusion of this paper in Section 5.

2. Related Work

Aboobaker & Ilavarasan [4] describe two methods for obtaining social media data for sarcasm detection: using existing datasets from other researchers or collecting data from social media. The first method described uses existing datasets that other researchers have already compiled. For example, Mehndiratta & Soni [5] utilized three publicly available datasets (Sarcasm Corpus V2 [6], ACL Irony Dataset [7], and News Headlines Dataset for Sarcasm Detection [8]) to evaluate various machine learning models along with standard and hybrid deep learning models across various standardized datasets. Meanwhile, AbuFarha and Magdy [9] have combined the existing public Arabic sentiment analysis dataset, namely SemEval's 2017 [10] and ASTD [11], by reannotating and adding sarcasm and dialect labels to produce a new Arabic sarcasm dataset called ArSarcasm. This method can save time and resources since the data has already been collected and annotated. However, the quality of the data may vary depending on the original dataset's quality and relevance to the researcher's specific needs. The original dataset may contain errors, biases, inconsistencies, or outdated, which can affect the accuracy of the findings. Therefore, it is important for researchers to carefully evaluate the quality and relevance of the existing dataset they want to use.

The second method described is collecting data directly from social media platforms. This approach involves collecting data directly from platforms like Twitter, Facebook, or Reddit, allowing researchers to create a more specific dataset for their research question. This method provides more relevant and high-quality data tailored to the research question. For example, a researcher may want to focus on sarcasm in tweets related to a specific topic, event, or language. On top of that, researchers have control over the data collection process and can ensure that ethical considerations, such as data privacy and informed consent, are appropriately addressed. The setback for this approach is that the process typically involves collecting and annotating a large amount of data, which can be time consuming and require significant effort and resources. Suhaimi et al. [3] have listed several previous studies on sarcasm detection in languages other than English. It was found that almost all those on the list that focuses on studying sarcasm detection in languages other than English will develop their own datasets from scratch due to the lack of free resources. This shows that language and cultural factors also influence the development of a sarcasm dataset because using a dataset developed for English may not be applicable or accurate for detecting sarcasm in other languages and cultures.

3. Methodology

The MalaySarc dataset is a resource for detecting and understanding sarcasm in the Malay language. In this section, we outline the methodology used to construct the MalaySarc dataset, which involves three main phases, as illustrated in Fig. 1. The initial stage entails data collection, which encompasses sourcing data from social media platforms focusing on Facebook. The second phase is data filtering, which requires careful selection of the most relevant data to ensure the dataset is focused and free of noise. Once the dataset is filtered, the final and most critical stage is data annotation, where human annotators manually label the data as either sarcastic or not sarcastic. This annotation process requires expertise and precision to ensure the data is labeled accurately, consistently, and reliably.

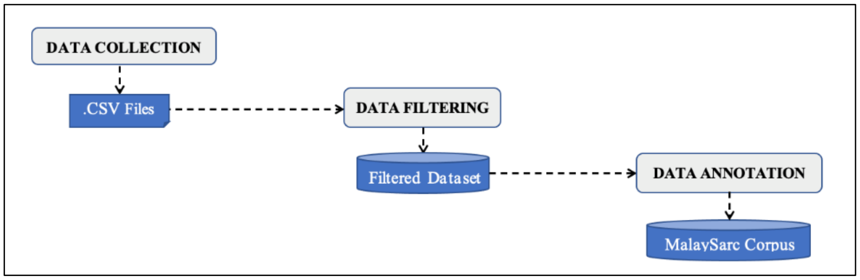

Fig. 1: Workflow for sarcasm dataset construction.

3.1. Data Collection

In this study, we aimed to collect Malay language data on Facebook comments related to COVID-19 in Malaysia. To ensure the reliability and accuracy of our dataset, we collected the data from scratch using Facepager, an application for social media data retrieval developed by Jünger and Keyling [12]. We specifically focused on Facebook's emotion reaction feature, allowing users to react to posts and comments with various emoticons. By focusing on comments and their associated emotion reactions, we captured a more comprehensive view of user sentiment toward COVID-19 in Malaysia. Collecting data from scratch also gave us greater control over the quality and quantity of the data and ensured that the dataset was relevant to the research focus. We believe that this data collection approach can serve as a valuable workflow for future studies that aim to collect data on user sentiment from social media platforms, especially for the Malay language domain. Fig.2 describes the workflow for data collection to retrieve the Facebook dataset.

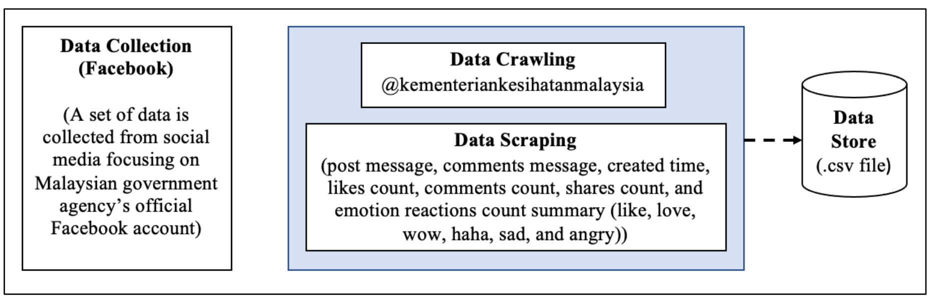

Fig. 2: Workflow for Data Collection to Retrieve Facebook Dataset.

3.2. Data Filtering

The initial data analysis stage involves filtering, which focuses on selecting only the relevant rows and columns from the raw dataset that meet specific criteria. The primary objective of this activity is to eliminate extraneous data, resulting in a more streamlined and manageable dataset. In order to create the preliminary dataset, we performed filtering in .csv format. The process involved deleting unnecessary columns from the original files to obtain the required data for the study. Subsequently, the filtered data from the three types of files were combined into a single file and saved as a new dataset. Out of the 11,461 comments crawled from the Ministry of Health (MOH) Facebook account, several were irrelevant and had to be filtered out before being used as a dataset. Specifically, 713 data were filtered out due to null text, hashtag, and link, while 230 data were marked as spam. Additionally, 519 data were removed as they were written in languages other than Malay. The remaining 9,999 filtered comments of the dataset will serve as the basis for the next step of the process, which involves data annotation.

3.3. Data Annotation

In this phase, the aim is to create a dataset of text examples labeled as either sarcasm or non-sarcastic by identifying the sentiment of the text. The labelling process benefits researchers in understanding the data, significantly contributing to the machine learning algorithm's learning process, hence improving the classification task [13]. Researchers commonly use two annotation methods to build a dataset for sarcasm detection: distant supervision and manual annotation [14]. Distant supervision is a good option when a large-scale dataset is required, as it can be automated without the need for human involvement. The texts are considered sarcastic if they meet predefined criteria, such as containing specific tags or being posted by specific social media accounts. For example, researchers may use hashtags like #sarcasm or #irony on such as Twitter, Reddit, or Amazon to automatically label text examples. This method allows the construction of large datasets without manual effort, but the labels produced can be noisy. On the other hand, manual annotation is an alternative to distant supervision, where texts are presented to human annotators for labelling. This method results in more accurate labels but requires manual effort where human annotators carefully evaluate and verify the labelling based on a shared understanding of sarcasm. While this approach is more accurate than distant supervision, it can be more time-consuming and resource intensive.

The manual annotation approach was selected in this study because the main focus was to gain a comprehensive understanding of the sarcasm features used by Malay language social media users without disregarding any potentially valuable data. The MalaySarc dataset was annotated using '0' and '1' for binary classification of sarcasm detection, where '0' represents non-sarcastic comments, and '1' signifies sarcastic comments. Two annotators, selected for their Malay fluency and understanding of sarcasm, reviewed each text and assigned the appropriate label according to annotation guidelines. To ensure the accuracy and consistency of the annotation, the annotators independently label each text. Discrepancies were resolved through discussion, and the final decision on the polarity of each text was determined using the majority voting method based on the three annotations. This quality control measure helps to ensure the annotated dataset's reliable and valid. Based on the result of the annotation process, from the remaining 9,999 filtered comments of the dataset, only 7,705 comments were deemed relevant for the study, as they either had positive or negative polarity, indicating the presence of sarcasm. The remaining 2,294 comments were deemed meaningless for developing a sarcastic dataset. This process demonstrates the importance of carefully selecting relevant data for analysis to achieve meaningful and accurate results.

4. Dataset Analysis

This section will provide a detailed discussion of the annotated MalaySarc dataset. Through the outcome of this descriptive analysis, a meaningful insights are gained from the data, which provided a better understanding of the data in the MalaySarc dataset, particularly with the expression of sarcasm.

4.1.Tables and Figures

The MalaySarc dataset comprises a range of comment lengths, from a minimum of 2 words to a maximum of 259 words. On average, the comments are 15 words long, suggesting that the dataset contains a mix of both short and longer comments. Fig. 3 shows the length frequency distribution of the entire dataset. The x-axis represents the length of the comments, and the y-axis represents the frequency of comments with that length. The length of the comments has been limited to 100 words to provide a more precise visualization of the distribution. The dataset presents a diverse range of comment lengths, with most comments falling within (0-30) word range.

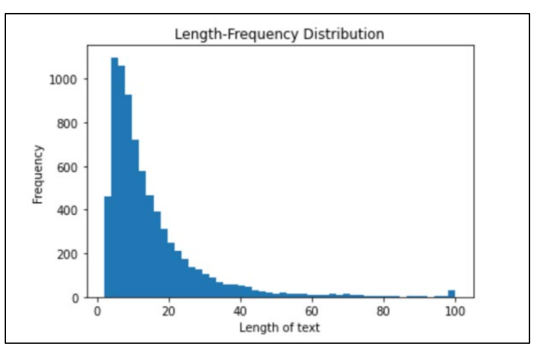

Fig. 3: Distributions of Comment Lengths in the MalaySarc Dataset.

Out of a total of 7,705 comments, 6,325 were identified as non-sarcastic, comprising 82%. While the remaining 18%, 1,380 comments, are classified as sarcastic. The statistic indicates that the data is highly unbalanced, where only a relatively small proportion of the comments analyzed contained sarcasm. However, identifying these sarcastic comments is crucial in comprehending the usage of sarcasm in Malay-language social media discourse. The next challenge is training a machine learning model to detect sarcasm with such an unbalanced dataset. The model developed must not be biased towards the majority class (non-sarcastic comments), as it can lead to difficulty accurately identifying the minority class (sarcastic comments). This misclassification can result in lower accuracy and a higher probability of mistakenly labeling sarcastic statements as non-sarcastic, ultimately affecting the model's reliability. According to Liu P et al. [15], different approaches can solve the imbalance issue in machine learning models. At the data level, over-sampling and under-sampling are used to balance class populations by replicating minority samples or eliminating majority samples, respectively. At the algorithmic level, cost-sensitive learning, one-class learning, and ensemble learning are proposed as solutions. This factor is crucial for ensuring the balance of the data set and its potential impact on the sarcasm detection model performance that will be developed later.

Table 1: Summary of MalaySarc dataset.

	Non-sarcastic	Sarcastic	Total
Number of comments	6,325	1,380	**7,705**
Number of words	97,554	16,807	**114,361**
Number of unique words	21,670	6,283	**24,884**

Table 1 provides frequency analysis on the MalaySarc dataset, which contains a collection of comments labeled as sarcastic or non-sarcastic. The first column indicates the number of comments in each category. There are 6,325 comments labeled as non-sarcastic and 1,380 comments labeled as sarcastic, for a total of 7,705 comments in the dataset. The second column shows the total number of words in each category. Non-sarcastic comments contain 97,554 words, while sarcastic comments contain 16,807 words, totaling 114,361 words in the dataset. The third column shows the number of unique words in each category. Non-sarcastic comments contain 21,670 unique words, while sarcastic comments contain 6,283. However, 3,069 words are common to both categories. Therefore, the dataset's total number of unique words is 24,884 (21,670 + 6,283 – 3,069). These statistics provide insights into the size and characteristics of the MalaySarc dataset, which can help understand and analyze the comments in the dataset.

4.2. Informal Text

During the manual annotation process, we observed that the MalaySarc dataset contained many noisy comments characterized by the usage of informal text, such as short form, slang words, and misspellings.

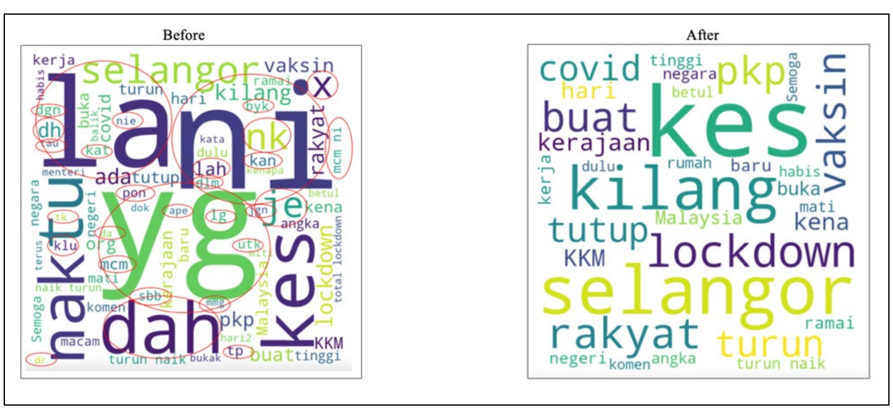

Fig. 4: A visualization of key theme in the MalaySarc dataset.

Fig.4 is evident from the word cloud visualization, which shows that these noisy comments are dominated by a small number of highly frequent and often misspelled Malay stopwords. The left image (before) refers to the word cloud dominated by Malay stopwords that use shortforms or incorrect spellings. These noisy comments can make it challenging to identify and classify the sarcasm in the comments accurately and may require additional preprocessing or cleaning steps to improve the data quality. As a result of this experiment, the Malay stopwords list has been revised to include commonly used shortforms and misspelled words. The Malay stopwords updated list has been used to clean the MalaySarc dataset, leading to a more accurate representation of key themes in word cloud visualization, as shown in the right image (after).

4.3. Sarcasm Features

In developing the MalaySarc dataset, the sarcasm feature was carefully considered and analyzed through a meticulous manual annotation process that examined the frequency of features commonly used in Malay social media, including words, emojis, and reactions to emotion reaction buttons. The resulting dataset provides diverse examples of sarcasm that consider the linguistic and cultural nuances of the Malay language, thus improving the accuracy and reliability of sarcasm detection. By selecting appropriate features, researchers can develop more effective algorithms for sarcasm detection, leading to a better understanding of social media communication and its impact on different groups. In this paper, we focused on analyzing three sarcasm features: emoji in text, Facebook emotion reaction button, and pattern-based feature that identifies high-frequency terms in the text. Repeated words in the same order are a sign of this pattern.

4.3.1 Emoji in text

Emojis can provide additional context and cues that can help identify the sarcastic tone of a message. For example, a person using a smiling face emoji while making a negative comment could be an indication of sarcasm. Emojis can also convey sarcasm directly, such as using the *"rolling eyes"* or *"face with tears of joy"*. Mubarak et al. [16] highlighted that using emojis can help identify offensive content and overcome challenges posed by non-standard spellings and language-dependent knowledge. This can improve accuracy and reliability, especially in multilingual or cross-cultural contexts. Within the MalaySarc dataset, a comprehensive examination of 7,705 comments reveals that 1,071 comments use at least one emoji in their text. Significantly, 358 comments have been recognized as containing sarcasm, contributing to 33.43%. These numbers indicate that there is substantial potential for individuals to use emojis as a tool for expressing sarcasm. Fig. 5 shows the clustered frequency distribution of emojis used in the MalaySarc dataset, which contains comments from social media in Malaysia labeled with their sarcasm status (0 for non-sarcastic and 1 for sarcastic).

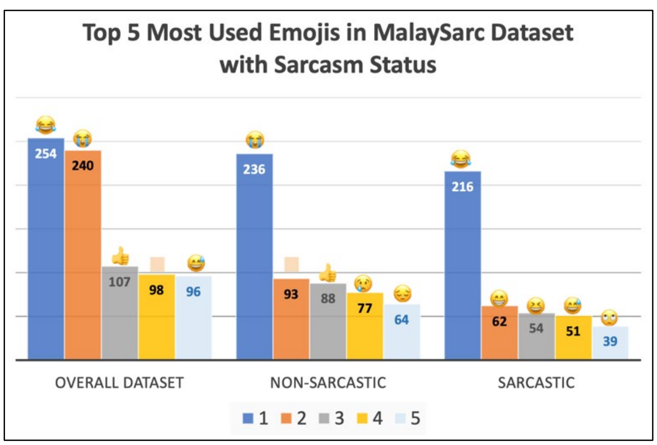

Fig. 5: Top 5 most used emojis in MalaySarc dataset with sarcasm status

The chart shows the top 5 most frequently used emojis in the dataset and separates them by sarcasm status (0 or 1). From the output, we can see that the most frequently used emoji in the entire dataset is "□" (a laughing face), followed by

"□" (a crying face), "□" (a thumbs up), "□" (a skin tone modifier), and "□" (a grinning face with sweat). When we look at the frequency of emojis by sarcasm status, we can see some differences in the top 5. For non-sarcastic comments (status 0), the most frequently used emoji is "□" (a crying face), followed by "□" (a skin tone modifier), "□" (a thumbs up), "□" (a crying face with tears), and "□" (a pensive face). On the other hand, for sarcastic comments (status 1), the most frequently used emoji is "□" (a laughing face), followed by "□" (a grinning face with smiling eyes), "□" (a grinning squinting face), "□" (a grinning face with sweat), and "□" (a face with rolling eyes). In summary, the use of emojis in non-sarcastic comments may vary depending on the topic being discussed. In the case of the MalaySarc dataset, which focuses on the Covid-19 pandemic, non-sarcastic comments tend to use emojis with somber or distressing emotions. However, it is noteworthy that the analysis focused on emojis that convey sarcasm, which aligns with a previous study [17] that categorized sarcasm as a wit to bring humor. Interestingly, this dataset's top 5 emojis in sarcasm comments are characterized by happy or amusing emotions.

4.3.2 Facebook emotion reaction button

Social media platforms offer a convenient click-based reaction feature that allows users to respond quickly to content without textual expression. This feature resembles textual emojis, which employ pictograms to convey emotional responses. For example, the Facebook application has click-based reactions consisting of six emotions (Like Love, Wow, Laughter, Anger, and Sad) [18], as shown in Fig. 6.

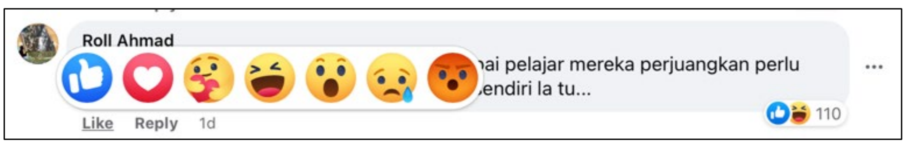

Fig. 6: Facebook click-based reactions featuring six emotions: Like, Love, Wow, Laughter, Anger, and Sad.

These reactions are simple and easy to use. They also allow users to express their emotional reactions to posts and comments shared on social media. Consequently, click-based reactions have become an essential feature of social media platforms, providing users with an efficient and effective way to interact with content without requiring lengthy or complex textual expressions.

Table 2: The total count of each emotion reaction based on sarcasm status.

Sarcasm	Facebook Emotion Reaction					
	like	*love*	*wow*	*haha*	*sad*	*angry*
0	10,327	105	67	362	249	36
1	1,129	10	20	861	34	13

Table 2 shows the total count of each reaction (*like, love, wow, haha, sad,* and *angry*) for two categories of comments based on their sarcasm status: non-sarcastic (sarcasm = 0) and sarcastic (sarcasm = 1). For example, in the non-sarcastic category, there were a total of 10,327 comments that received a like reaction, 105 comments that received a love reaction, 67 comments that received a wow reaction, 362 comments that received a *'haha'* reaction, 249 comments that received a *'sad'* reaction, and 36 comments that received an *'angry'* reaction. In the sarcastic category, there were a total of 1,129 comments that received a *'like'* reaction, 10 comments that received a *'love'* reaction, 20 comments that received a 'wow' reaction, 861 comments that received a *'haha'* reaction, 34 comments that received a *'sad'* reaction, and 13 comments that received an *'angry'* reaction. Overall, the total count of reactions for the sarcastic category is much lower than the non-sarcastic category, possibly due to a smaller sample size or the tendency for sarcasm to be less commonly used in comments than non-sarcastic expressions. Additionally, the *'haha'* reaction is much more commonly used for sarcastic comments than other reactions, supporting the hypothesis that *'haha'* reactions may be more closely associated with sarcasm.

4.3.3 Pattern-based feature

While analyzing the MalaySarc dataset using word cloud, we have focused explicitly on sarcastic comments and narrowed down the word cloud to display words commonly used in sarcastic comments, as illustrated in Fig. 10.

Fig. 7: A visualization of common words used in sarcastic comments from the MalaySarc dataset.

Our analysis of the MalaySarc dataset using word clouds focused on identifying phrases and words commonly used in sarcastic comments. The word cloud has revealed an intriguing finding, highlighting some of the sarcastic comments, including lines from the movie and song's lyrics that are widely popular in Malaysia. One phrase highlighted with a red box on display is *"abg Jamil"*, which refers to a popular script in a Malay satirical comedy film called *"Madu Tiga"*. The script features the phrase *"...sampai abang jamil mampus"* and is often used sarcastically to describe a never-ending situation. Table 3 shows examples of sarcastic comments found in the dataset that uses the phrase.

Table 3: Examples of sarcastic comments using the phrase "abg jamil" in the MalaySarc dataset.

Id	Comments	Sarcasm
1034	Bt lockdown ibarat kunci pintu dpan, bukak luas2 pintu blakang. Hurmm... Jom la smbung lockdown smpai abg jamil......	1
2670	lockdown sampai abg jamil mampos□□	1
4172	Slagi kilang^2 xtutup sampai abg jamil ampossss pon xturun kes	1
6665	Sampai abg jamil mati hidup balik pon xkan kurang laa kes cobik ni...lolok2down pon x macam untuk kurangkan kes sebenarnya	1
7380	Sampai abg jamil mampus kes takkan turun selagi kilang kilang besar beroperasi□	1

Other commonly used phrase identified through our analysis is *"turun naik" and "naik turun"*, a lyric from the viral song *"Turun Naik Oles Trus"* by Fresh Boy ft. Blasta Rap Family. The lyric *"Ko turun naik, Ko turun naik, Ko turun naik lagi"* is repeated in the song and has become a popular cultural reference for sarcastic comments in a more humorous tone on Malay social media platforms. Table 4 shows a sample of sarcastic comments found in the dataset that uses the phrase. Our analysis suggests that cultural factors, such as the use of popular media like movies and songs, can influence the use of sarcasm in comments.

Table 4: Examples of sarcastic comments using the phrase “turun naik” and “naik turun” in the MalaySarc dataset.

Id	Comments	Sarcasm
2260	Turun naik turun naik..□□□□□.. lockdown mnyusahkan rakyat.	1
3081	Naik turun naik turun, kutinggal turun naik, dah macam lagu. Lockdown 4 minggu pun xde perubahan□□□□	1
5070	naik turun naik turun sampai abg jamil mampos	1
6943	Angka turun naik turun naik apa cita. Macam main jongkang jongkit pulak □□	1
7513	Aku nk nyanyi Turun Naik Turun Naik□□□humm xpala tulis jalaa□□	1

4. Conclusion

Creating a dataset for sarcasm is a complex task due to the contextual variability of sarcastic language, which makes it challenging to identify and label sarcastic statements without considering the context in which they are used. This variability is further complicated when dealing with languages other than English, as the identification of sarcasm can be subjective and varies based on individuals' cultural, linguistic, and personal backgrounds. Therefore, annotators who share a common cultural background with the author of the text are more likely to identify the sarcasm content correctly. It is crucial to address these challenges when creating sarcasm datasets to ensure that the resulting datasets are reliable and applicable across different contexts. Additionally, incorporating advanced machine learning techniques and natural language processing algorithms can help overcome some limitations of human annotation, providing more accurate and reliable results.

This dataset analysis shows that emoji is one of the features that play an essential role in determining sarcasm. However, not all messages include emojis, so relying solely on them as a feature may not capture all instances of sarcasm. Therefore, while using emojis as a feature can be helpful in some cases, it should be used in combination with other features, such as context and linguistic patterns, to achieve more accurate sarcasm detection. In the context of this dataset, the presence or absence of a 'haha' emotion reaction may be one factor to consider when trying to predict whether a comment is sarcastic or not. However, it is unlikely to be the only factor or a definitive indicator of sarcasm.

The resulting dataset provides diverse examples of sarcasm that consider the linguistic and cultural nuances of the Malay language, thus improving the accuracy and reliability of sarcasm detection. By selecting appropriate features, researchers can develop more effective algorithms for sarcasm detection, leading to a better understanding of social media communication and its impact on different groups. Overall, constructing a high-quality sarcasm dataset is a time-consuming and challenging process that requires careful planning, attention to detail, and a thorough understanding of sarcasm's underlying linguistic and cultural nuances.

The MalaySarc dataset provides a valuable resource for further research, enabling researchers to develop and test new methods for detecting sarcasm in social media communication. The resulting corpus is expected to help analytical studies related to sarcasm, especially in identifying sarcasm through machine learning techniques. In future work, we will continue to explore the MalaySarc dataset by developing and evaluating sarcasm detection model for the Malay language. The model can enhance the accuracy of sarcasm detection and facilitate a more efficient and effective analysis of social media communication.

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