Proposing Malay Sarcasm Detection on Social Media Services: A Machine Learning Approach

Article history

Received:
12th October 2021

Received in revised form:
18th October 2021

Accepted:
28th October 2021

Published online:
11th November 2021

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Abstract

User comments from social media platforms have become crucial inputs for organisations, especially the government, to get feedback about their programs and services. However, since people can respond freely on social media sites, sometimes they like to use sarcastic texts implicitly in conveying their disagreeing views. Research on sarcasm detection for other languages such as the Malay language is still in its early stages. The use of noisy text, mixed languages and slang words by social media users has increased the difficulty of classifying sentiments in the Malay language. Thus, this paper proposes a Malay sarcasm detection model on social media based on a machine learning approach. The proposed model will also leverage the emotion reaction button of the Facebook platform as one of the main features to be used in sarcasm detection.

Keywords: *sarcasm detection, sentiment analysis, machine learning, social media platform, Malay corpus*

1. Introduction

People tend to express their honest opinions and feelings about any topic on social media. For example, dissatisfaction with certain products, services, or excitement over positive events. The increasing use of social media is an opportunity for organisations such as the government or business companies to act proactively in obtaining public feedback related to products, services, or new policies. All the feedbacks and comments are valuable input for organizations to improve their service delivery. However, since people can respond freely on social media sites, sometimes they like to use sarcastic texts implicitly in conveying their disagreeing views.

Sarcasm text may damage an organisation's reputation, and there's a chance that the comments might be used to distribute false news because people unable to differentiate the comments as satirical. Thus, to ensure the authenticity of the content, the social media text need to be analysed thoroughly to identify the existence of sarcasm elements. This can be achieved by applying the Sentiment Analysis (SA), a type of text mining that extracts and analysing people's responses and classifies whether they are positive or negative toward a particular topic [1].

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Sarcasm is among the biggest challenges in SA as the sarcastic pattern is usually the point contrary to written sentences. Based on the definition in Cambridge Dictionary [2], sarcasm refers to *"the use of remarks that mean the opposite of what they say, made to hurt someone's feelings or to criticise something humorously"*. Sarcasm detection is an essential task in natural language processing (NLP), especially in classification. The presence of sarcasm in a text can lead to misclassification [3] and affect the quality of SA.

Detecting sarcasm is crucial for avoiding misunderstandings and knowing people's true feelings [4]. Therefore, the analytical method must consider the aspects that contribute to sarcasm and find the patterns of similarity. Bouazizi and Ohtsuki [5] discovered those aspects throughout the data annotation process in their study. They have categorised sarcasm sentences into three purposes: sarcasm as i) a wit, ii) a whimper, and iii) an evasion. Sarcasm is considered as wit if the intention is to bring humour. Sarcasm as a whimper shows anger or annoyance, while sarcasm is an evasion when the person wants to avoid giving a clear answer. These purposes are categorised based on the forms of writing such as the use of capital letter words, exclamation, question marks, some sarcasm-related emoticons, using exaggeration positive expressions to describe negativity, use complicated sentences and uncommon words.

In verbal conversation, sentiment through facial expressions can be described in the form of emoticons. Therefore, using emoticons or emotion reaction buttons in communication in social media text is very popular nowadays because of its capability to make the conversation more relaxed, open, and easy for people to express their feelings [6]. This is another challenge for researchers in identifying sentiment expressed through emoticons and graphic icons. Researchers need to extract the semantic meaning and sentiment indicated in these emoticons and icons and then build a lexicon or train the flexible and comprehensive algorithms to determine sentiment orientations [7]. For example, users can use the reaction button on the Facebook page to convey various emotions related to thoughts, feelings, and sarcasm [8]. Facebook launched this feature in February 2016, allowing users to express specific emotions in response to a post or comment [9].

Techniques for sarcasm detection can be broadly categorised into four categories; rule-based approach, lexicon-based approach, machine learning-based approach, and deep learning-based approach [10]. The machine learning approach is more suitable for this study since it can adapt various features and labelled data for training sentiment classifiers. In contrast, the lexicon-based method has to rely on lists of words with predetermined emotional weight [11].

Hence, this study aims to fill the gap by developing a sarcasm detection model based on a machine learning approach by leveraging the emotion reaction of the Facebook platform as one of the main features to be used in sarcasm detection. In addition, a new public dataset for detecting Malay sarcasm will be developed, which will be useful for future research work. The remaining structure of the paper is organised as follows: Section 2 presents some related work on sarcasm detection in social media. Section 3 introduces the requirements and the development phases for Malay sarcasm detection. The paper is concluded in Section 4.

2. Related Works

There have been active research works on sarcasm detection on social media in recent years. Shrivastava & Kumar [12] shows how, in the past, sarcasm detection research was mainly focused on linguistic detection. Only after when the online website starts to evolve, this research laid the groundwork for computational detection. Tepperman [13] was among the earliest to apply the NLP method in sarcasm detection. He predicted sarcasm from speech transcripts by focusing on *"yeah right"* as a determiner of a sarcastic sentence. According to Babanejad et al. [14], computational sarcasm detection in the text has progressed from simple lexical and syntactic pattern models to more comprehensive models that consider advanced linguistic features such as positive predicates, interjections, gestural cues, or behaviour modelling. The most popular approach is machine learning like Naïve Bayes, Support Vector Machine, Random Forest, and Decision Trees. Only years recently, that deep learning-based approach has gained increasing attention, such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM).

Commonly, a sarcastic tone can be detected through intonation and gestures in a normal conversation verbally. However, these features are missing through the text-based communication that added more complexity in sarcasm detection [15]. Therefore, it requires a detailed process to detect sarcasm in social media to identify implied negative reactions. Several types of features in datasets have been explored and examined using different methods in sarcasm detection in previous studies. Chaudhari & Chandankhede [16] have categorised these features into six types, as shown in Table 1.

Table 1. Type of Features [16]

Type of feature	Description	Examples
Lexical	Includes text properties such as are unigrams, bigrams, etc. One of the common features using in NLP.	Unigram, bigram, n-grams, skip-grams, #hashtag, etc.
Pragmatic	Refers to symbolic and figurative texts. One of the powerful and key features for detecting sarcasm in textual data.	Emoticons, replies, emphatic, etc.
Hyperbole	The use of exaggeration as a figure of speech.	Intensifiers, interjection, quotes, punctuation, etc.
Pattern-Based	Refers to high-frequency words and content words based on their frequency of occurrence in the text.	Frequency of appearances of the word
Syntactic	Contain recurrent sequences of the morphosyntactic pattern (combination of morphology and syntax)	POS-grams and temporal imbalance etc.
Contextual	Refers to any information or common knowledge beyond the text to be predicted. It can be incorporated using supplementary data or information from the source platform of data	Annotators, etc.
Metaphoric	includes extreme positive or negative nouns, extreme adjectives, proverbs, honorifics, etc.	Extreme positive or negative nouns, extreme adjectives, proverbs, honorifics etc.

Since Facebook's emotion reaction embedded feature is nearly identical to emoticons, we want to investigate and combine it with other elements in detecting sarcasm for this study. It is challenging to find previous studies that have focused on this feature in detecting sarcasm, given that most researchers concentrated on Twitter datasets. Even so, [17] were among the researchers who used Facebook reactions as emotional cues in their study as one of the features to detect sarcasm showing that the emotions are strongly tied to sarcastic expressions. This feature has yet to be widely explored, especially in detecting sarcasm using a Malay dataset from Facebook.

Researchers have worked on issues like slang, non-context features, and multilingual languages [18]. Previously, most studies of sarcasm detection have only carried out focusing on the English language. In the past few years, recent trends in detecting sarcasm have been observed in different languages. There were a few studies related to sarcasm detection focusing on languages other than English, such as Persian [3], Indonesia [6,19], Arabic [20], Malay [21], and so on.

According to Zabha et al. [22], the Malay language is still under-resourced since most research on sentiment analysis focuses on vocabulary in the English lexicon. Research on sentiment analysis in Malaysia's social media is complex due to the mixed use of English and Malay. A systematic literature review on sentiment analysis for the Malay language conducted by Handayani et al. [23] assures a strong reason for more research constructing sentiment analysis research specifically for the Malay language.

The sarcasm comments mostly shared on popular social media platforms such as Twitter and Facebook. Based on a review by Wicana et al. [24], most research on sarcasm datasets has been conducted on the Twitter platform compared to Facebook. However, Facebook has more comments and subscribers than Twitter [25]. This is perhaps, most studies focused on the short text datasets rather than analysing long text datasets. Therefore, this proposed work explores a new context in analysing the long text dataset: Facebook comments to detect sarcasm. The focus is on Facebook comments from Malaysia or using the Malay Language.

3. The Model Development Phases

In proposing the Malay sarcasm detection on social media, it will involve six development phases using Cross Relation Industry Standard Process for Data Mining (CRISP-DM) [26] model: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. The CRISP-DM methodology is a well-established and robust methodology that provides a structured way to create a data mining project. The illustration of the operational framework for is provided in Figure 3.1.

3.1 Phase 1: Busines Understanding

The first phase is to do a preliminary study about the research topic. Several literature reviews are conducted to clarify and focus on the research problem and broaden the knowledge base. Issues and problems related to sarcasm detection in social media were collected and analyzed through past studies. Study gaps were identified based on the literature reviews conducted.

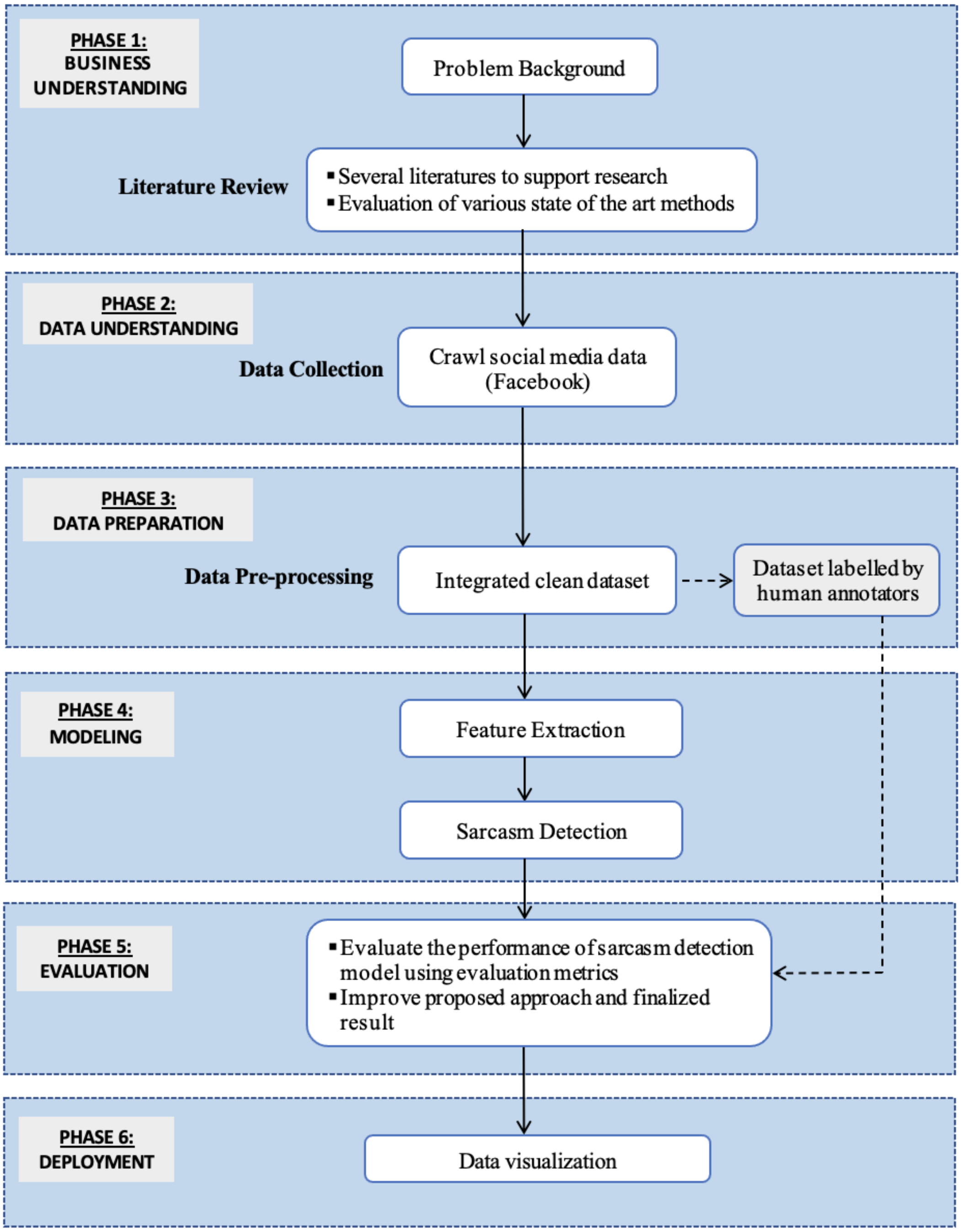

Figure 1. Proposed Model Development Phases

3.2 Phase 2: Data Understanding

This phase begins with the preliminary data collection. The data for this research is collected near real-time from Facebook posts and comments using Facebook Graph API and FacePager, a data crawler to extract social media data. All the retrieved data are saved in a .csv file once the data crawling process is done. For this research, an official Facebook page account for the Malaysian National Security Council (MKN) and Ministry of Health Malaysia (MOH) is selected. The duration for data collected will be from (01/09/2021 until 31/12/2021). The pages have many followers where the public actively gives their comments and feedback. The selection is also to support the scope of the study, which will focus on how government management in dealing with crises. Data extracted from Facebook for this research consists of the following variable such as post message, comments message, created time, likes count, comments count, shares count, and emotion reactions summary, which includes six (6) categories of reaction (like, love, wow, haha, sad, and angry).

3.3 Phase 3: Data Preparation

The data preparation phase covers all activities to construct the final dataset from the initial raw data. Then, pre-processing is conducted to ensure the proposed model's dataset is accurate, relevant, and usable. The data pre-processing is essential to produce a clean dataset to work with the machine learning algorithm. Handling noisy text containing spelling errors, non-standard words, style words, short-form words, and repetition is a big challenge in data pre-processing for social media, especially for the Malay language. Accordingly, the accuracy of the classification process is highly dependent on the extent to which the text can be refined. Stop word, stemming, tokenisation, punctuation, and POS-tagging are among the most commonly used pre-processing techniques by researchers [27].

In this phase, the dataset will also be manually labelled sarcastic or not sarcastic by identifying the sentiment of the text based on selected features. The labelling process is beneficial to researchers in understanding the data, making a significant contribution to the machine learning algorithm's learning process, hence improving the classification task [28]. A properly annotated dataset will be the objective standard so that the accuracy and quality of the trained model will be determined based on the ground truth.

3.4 Phase 4: Modelling

This phase is the core and critical stage in a machine learning project. The modelling phase includes choosing a modelling technique, designing a test case, and creating a model [29]. Specific parameters must be set to build the sarcasm detection model. There are two crucial activities in this phase which are feature extraction and sarcasm detection.

3.4.1. Feature Extraction: Feature extraction is a method for reducing the number of resources used to describe a dataset by converting the input data into a series of features. The goal is to find the most relevant features so that those selected features to be trained to a classification model. It is considered one of the most critical tasks in detecting sarcasm, especially when handling a large dataset. Feature extraction helps to improve accuracy over the prediction and speed up the training process. This procedure will retrieve pertinent data from the sarcastic dataset, which will aid in the training of the sarcasm detection model [30]. Authors of [16] suggested that future research should look into new features and combine them with the existing features to improve accuracy. The suggestion is in line with the proposed research, concentrating on four types of features: lexical, pragmatic, hyperbolic, and metaphorical. These features include Facebook's emotional reactions as a new feature to be explored since no researchers have yet investigated the Malay language corpus.

In addition, for the lexical parts, we will consider two distinctive features introduced by Chekima & Alfred [31] by using the RojakLex lexicon to improve the SA accuracy of Malay social media text. The two features are *Bahasa Rojak* (Mix Language) and *Bahasa SMS* (Short Message Service language).

i) *Bahasa Rojak* is a Malaysian mix of combinations between two or more of the most used languages. For example, *"Sektor industri wajib lockdown juga, no excuse. Baru kes boleh stop*". This sentence consists of two languages Malay and English *(underlined).*

ii) *Bahasa SMS* is a short form language used to communicate via SMS channels, the vocabulary employed is typically non-standard or informal. For example, *"Jgn asik salahkan rakyat x ikut SOP.tutup kilang2 tu baru blh turunkan kes"*. The highlighted words are considered *Bahasa SMS* and must be adequately tackled.

3.4.2. Sarcasm Detection: In this phase, classification techniques will be implemented for sarcasm detection. For this study, we will use a machine learning supervised learning approach to train the models. Sarcasm detection is considered a binary classification task, with extensive features manually constructed over input documents [32]. In most binary classification problems, one class represents the normal state (e.g., *'not sarcastic'*) while the other represents the abnormal state (e.g., *'sarcastic'*). There are two steps in this phase; 1) train the model classifiers on the training datasets with the selected features obtained from the feature extraction techniques, then 2) the trained classifiers will predict whether the Facebook comments are sarcastic or non-sarcastic using the test data. Naïve Bayes, Decision Trees, Support Vector Machine (SVM), Logistic Regression, and k-Nearest Neighbours (KNN) are popular algorithms used for binary classification.

3.5 Phase 5: Evaluation

In this phase, the proposed model needs to be tested to measure the performance of the developed model. The proposed model will be validated based on the results from testing data and compared with the results from the annotated dataset, which annotators have manually labelled in the early phase. For this research, the evaluation will calculate the accuracy, precision, recall, and F1-score of the proposed sarcasm detection model using k-fold cross-validation. K-fold cross-validation is a statistical method usually applied in machine learning to estimate the model's skill on new data by sampling a subset of data to do model training and the remaining subset of data to do model validation. It is an effective solution to avoid over-fitting issues when using a limited data sample [33].

3.5.1. Accuracy: *Accuracy* is defined as the ratio of accurately predicted samples *(i.e., both True Positives + True Negatives)* to the total number of samples. It measures how well the proposed model performs [34].

Accuracy = (*TP + TN) / (TP + FP + FN + TN)*

3.5.2. Precision: *Precision* is defined as the ratio of accurately predicted positive samples *(i.e., True Positives)* to the total number of samples classified as positive *(i.e., both True Positives + False Positives)*. The *Precision* value indicates how reliable the model is at classifying *Positive* samples.
Precision = TP / (TP + FP)

3.5.3. Recall: *Recall* is defined as the ratio of accurately predicted positive samples *(i.e., True Positives)* to the actual total number of *Positive* samples *(i.e., both True Positives + False Negatives)*. The *recall* only considers the positive samples in its calculation. When the recall value is high, it shows that the model has the reliable ability to detect positive samples.

Recall = TP / (TP + FN)

3.5.4. F1-score: *F1-score* or *F-measure* is defined as the weighted average of *recall* and *precision*. This variant is best measured when dealing with the imbalanced dataset [34].

*F1-score = (2 * Precision * Recall) / (Precision + Recall)*

3.6 Phase 6: Deployment

With the completion of the evaluation process, the findings will be interpreted and discussed. The mined data is represented using data visualization such as reports, tables, and other visual representations. The presentation of the outcomes should meet understandably and adequately.

4. Discussion

The study by Aboobaker & Ilavarasan [10] highlights a few challenges in sarcasm detection. First, understanding and decrypting the real meaning of the ambiguous nature of sarcastic words. It is challenging because a sarcastic phrase usually conveys a negative message by using the only favourable word. Second, it is more difficult to detect sarcasm from the text than speech because speech features like tones, body gestures, and facial expressions are not present. Third, the quality of the dataset is also crucial to correctly detecting sarcasm. The dataset without a hashtag is more complicated to understand. Fourth, the researchers also need to consider suitable features to be extracted and trained for the classification model. Selecting appropriate features can increase the accuracy of sarcasm detection. The features frequently used by previous researchers are n-gram, hashtag, semantic, syntactic, POS-tagger, and Bag-of-Word [27]. It shows that the emoticon or emotion reaction feature has not yet been widely exploited. In contrast, this feature is significant because it can describe facial expressions that represent feelings in the sentences presented.

Finally, choosing the proper classification technique is also essential for categorising sentences into non-sarcastic and sarcastic. The proposed work approach helps find the relationship between emotional reactions and user comments to create an automated annotation process [30] and enable a faster filtering process and detecting sarcasm. Besides, we will examine the potential of using Facebook reactions to recognise and classify whether the sentence is sarcastic or not.

5. Conclusion

In conclusion, this paper highlighted the background of sarcasm detection in sentiment analysis, the most common approaches used in sarcasm detection, and the growing research areas of sarcasm detection on social media in languages other than English. In addition, the proposed model development phases, and challenges in detecting sarcasm have also been discussed. Based on preliminary findings on this topic, we propose a Malay sarcasm detection model on social media based on a machine learning approach. In particular, the proposed study may improve the feature extraction process by considering the emotion reaction feature as one of the main features in detecting sarcasm. Besides, a new public dataset for Malay sarcasm detection will be created for future research work.

Acknowledgments

There was no specific grant for this research from any funding source in the public, private, or non-profit sectors.

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