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DOES GOOGLE TRANSLATE AFFECT LEXICON-BASED SENTIMENT ANALYSIS OF MALAY SOCIAL MEDIA TEXT?

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ABSTRACT

There are a lot of sentiment resources for English, however, there are limited resources in a resource-poor language like the Malay language. One approach to improving sentiment analysis is to translate the focus-language text to a resource-rich language such as English by using Machine Translation (MT). However, when text is translated from one language into another, sentiment is preserved to varying degrees. The objective of this paper is to assess the performance of MT in Google Translate towards sentiment analysis of Malay social media text on Facebook pages of a caregiver of a person with autism. A total of 3,525 Facebook comments in the Malay language were gathered from May to October 2020. The comments were manually translated to English to create dataset_manual. Google Translate was used to automatically translate the Malay comments into English creating dataset_auto. The sentiment polarity of each comment was labeled as a ground truth dataset. A lexicon-based approach was used to extract sentiment from both dataset_manual and dataset_auto to determine the sentiment polarity. Results show that 65.9% of sentiment analysis using dataset_auto significantly reduces sentiment analysis. The sentiment expressions are often mistranslated into neutral expressions when translated. Meanwhile, sentiment analysis using dataset_manual was still able to capture the sentiment of Facebook comment without taking the comment out of context where 92.5% shows positive sentiment towards comments related to autism spectrum disorder.

Keywords*: Facebook, Google Translate, Lexicon-Based, Machine Translation, Sentiment Analysis*

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1. Introduction

Sentiment or "tone" is part of communication science. It is generally expressed with ambiguous and creative language (Atteveldt *et al.*, 2021). Different languages have different ambiguities with different meanings. Thus, sentiment analysis in different languages poses a challenge. Sentiment analysis detects and classifies the emotional texts into classes of "positive", "negative" and "neutral" (Balahur, 2013; Razak *et al.*, 2018; Puteh *et al.*, 2013). "Emotional text" is a content that is mostly used in social media for many reasons. There are many sentiment resources essential for automated sentiment analysis such as sentiment labeled corpora, existing mainly in English. Although there is a growing need to analyze texts from other languages such as Malay, it cannot be done effectively with resource-poor language. Therefore, for the automated sentiment analysis of low resources languages, the focus language is translated to English resources and is used for automated sentiment analysis of text in that language.

Machine Translation (MT) models are designed to generate translations that carry the same meaning as the original sentence. It is also fluent in the target language. However, in some cases, metrics for measuring fluency are less relevant. This is the scenario in the sentiment analysis of translated sentences, where maintaining the sentiment is the priority, even if the translation is not accurate in terms of adequacy and fluency (Tebbifakhr *et al.*, 2019). However, despite the MT system generating understandable translations, it might not manifest the same sentiment as the original sentence. Automatic translation of sentiments is difficult due to the variation of meaning in a certain vocabulary (Poncelas *et al.*, 2020). There have been contradicting results in the use of automatic translation for sentiment analysis. Balahur and Turchi (2014) in their studies on assessing the performance of statistical sentiment analysis techniques on machine-translated texts concluded that sentiment analysis can be performed on automatically translated texts without a substantial loss in accuracy. They studied the possibility of using Google, Bing and Moses MT systems for semantic analysis in English, German, Spanish and French languages. They further used machine learning meta-classifiers to alleviate the noises produced by the MTs. Barhoumi *et al.* (2018) also supported the use of Moses MT for achieving competitive performance in semantic analysis of Arabic content translated into English. They believed that MT can successfully transfer the sentiment polarity. However, contrary to the above-mentioned studies, Lohar *et al.* (2017) cautioned the use of MTs may not be suitable for all languages, especially for the language of a low resource. They stated that the use of wrong MT has led to the lowest translation evaluation and sentiment preservation scores.

Therefore, this paper investigates the performance of a popular MT that is Google Translate on Malay language sentiment analysis of social media text. Social media has become an important supporting platform for caregivers of people with autism (PWA) to seek knowledge, understand children's behavior, and managed their feelings in coping with this situation (Rofiza and Jazredal, 2021). There are many types of social media for autism support groups that may serve valuable knowledge, tips, and motivation from all over the world. The sentiment from the social media's comment(s) may indicate the readers' reactions like attitudes, emotions and opinions towards the social media's owner (Saiful Bakhtiar *et al.*, 2019). Nevertheless, this high volume of data requires an automatic mechanism to extract and translate so that everyone all around the world could benefit from it.

As early as 2008, Google Translate has been used in semantic analysis (Wan, 2008) to identify the polarity of 886 Chinese product reviews. The individual analysis of the translated English reviews outperformed the individual analysis of the original Chinese reviews, and the combination of the individual analysis results further improved the performance. Google Translate has also shown to be a useful tool in automated text analysis using bag-of-words text models (De Vries *et al.*, 2018). Results using official European Parliament debate transcriptions in five EU languages showed that at both document and corpus levels, the term-document matrices were highly similar, with minor differences across languages. There was also considerable overlap in the set of features from texts translated by humans and machines. A most recent work done by Saadany *et al.* (2021) investigated the use of Google Translate as a real-life utility to transfer emotions in user-generated (UGC) multilingual data (i.e. Twitter). They experimented with using Arabic, Spanish and English languages and concluded that the use of Google Translate may be counter-productive. They also foresee the need for new evaluation metrics to measure the transfer of emotions in UGC data. The contribution of this paper is two-fold: 1) To the best of our knowledge, there is no work done to assess the consequence of Google Translate in the sentiment analysis of Malay text on social media (i.e. Facebook), and ii) What is the general sentiments of the Malay-spoken communities on autism spectrum disorder? Hence, this work studies the impact of translating Malay sentiments comments on Facebook, specifically on the caregiver of a PWA. In Section 2, we describe the related works on sentiment analysis and in Section 3, the methodology of this work is presented. Section 4 discusses the results and findings followed by the conclusion in Section 5.

2. Literature Review

Machine learning and lexicon-based are the two (2) main approaches in sentiment analysis that are used to classify the sentiment. The machine learning approach also known as the supervised approach employs machine-learning techniques namely Support Vector Machine (SVM), Neural Network (NN), Naïve Bayes (NB), Maximum Entropy (ME), and diverse features to construct a classifier that can identify text that expresses sentiment (Shamsudin, 2015). However, this approach requires large annotated training data to estimate model parameters; this is difficult for a low-resource language such as Malay. The lexicon-based approach also known as the unsupervised approach involves calculating an orientation of a text document from the semantic orientation of words or phrases in the document (Taboada *et al.*, 2011). This approach does not require a sufficient amount of human-annotated training data to obtain acceptable results (Almatarneh & Gamallo, 2018). It also was found to be practically feasible for automatically mining sentiments from unstructured data (Chaovalit & Zhou, 2005). Hence, a lexicon-based is the proposed approach for this study.

Sentiment analysis (SA) of Malay language social media texts has several challenges as it is a morphologically complex language. Also, there is very little work done on sentiment analysis in the Malay language (Chekima & Alfred, 2018; Shamsudin *et al.*, 2015; Zabha *et al.*, 2019). Based on the findings, five studies implemented a lexicon-based approach for Malay SA as shown in Table 1.

Table 1. Malay Sentiment Analysis using Lexicon-based Approach

Author	Features	Dataset	Types of language
Zamani *et al.* (2014)	Standard Method	Facebook Comments (emotions)	Unstructured Malay and English
Shamsudin *et al.* (2015)	Manual and Auto Lexical Dictionary	Facebook Comments (adjectives)	Unstructured Malay and English
Shamsudin *et al.* (2016)	Manual and Auto Lexical Dictionary	Facebook Comments (adjectives, verbs, adverbs, negation)	Unstructured Malay and English
Chekima & Alfred (2018)	Manual and Auto RojakLex	Social media text (Bahasa SMS, neologism)	Unstructured Malay and English
Zabha *et al.* (2019)	Lexicon-based approach	Twitter Data	Unstructured Malay and English

Zamani *et al.* (2014) used a lexical-based approach to analyze users' emotions in unstructured Facebook comments. They manually tagged the words with the emotion categories and then calculate the word frequency to classify the sentiment. The comments were classified as happy if the percentage of happy emotions was higher than unhappy emotions and vice versa. No MT system was used in this research.

Shamsudin *et al.* (2015) introduced a lexical-based method to analyze the sentiment of Facebook comments in Malay. They created two types of score dictionaries 1) Malay Adjective score dictionary and 2) Malay-English (BM-ENG) score dictionary. Commonly used Malay adjective words were extracted to construct the Malay Adjective score dictionary. Then, the words were manually categorized as positive (+1) and negative (-1). Meanwhile, SentiWordNet was used as the resource for building the Malay-English (BM-ENG) score dictionary. Three types of lexical-based techniques: 1) Term Counting, 2) Average on Comments, and 3) Term Score Summation was implemented in their study. Term Counting was solely dependent on the Malay adjective score dictionary while Average on Comments and Term Score Summation used both Malay Adjective and Malay-English (BM-ENG) score dictionary.

Shamsudin *et al.* (2016) improved the Malay Adjective score created by Shamsudin *et al.* (2015) by classifying the sentiment not only based on the adjectives but also verbs, adverbs, and negation and naming it a score dictionary. WordNet Bahasa has been used as the resource for creating the verb, adverb, and negation score dictionary. To classify the sentiment, two types of lexical-based techniques: 1) Term Counting and 2) Term Counting Average have been applied. A comment is classified as positive when the sentiment score value is positive and vice versa. The comment is classified as neutral if it has a sentiment score value of 0. They also did not utilize any MT in their research.

Chekima and Alfred (2018) constructed a RojakLex as a lexicon-based approach to handle unstructured Malay text and a human-centric approach for translating the neologism terms. MySentiDic was used for the English-Malay lexicon while for the Bahasa SMS lexicon, they utilized the rules proposed by Dewan Bahasa dan Pustaka. Valence shifter has been used in handling Bahasa Rojak effectively. The sentence was classified as positive if it contains more positive words compared to negative words and vice versa. No MT was deployed in their research.

Zabha *et al.* (2019) developed a cross-lingual sentiment analysis using a lexicon-based approach. Two lexicons of languages are combined in the system, then, the Twitter data were collected and the results were determined using a graph. The results showed that the classifier was able to determine the sentiments. This study is significant for companies and governments to understand people's opinions on social networks, especially in Malay-speaking regions.

3. Methods

There were four major stages involved in the research methodology: 1) data collection, 2) comments translation, 3) pre-processing and sentiment detection, and 4) sentiment analysis. As stated earlier, the main aim is to investigate the effect of Machine Translation (MT) on the sentiment analysis of the Malay language. The process involved in each stage is summarized in Table 2.

3.1 Data Collection

In this research, sentiments comments on Facebook pages of a caregiver of a person with autism (PWA) was chosen. The caregiver posted activities and incidents in the daily lives of his autistic son and his followers responded to the postings. Thus, a lot of emotions and sentiments were expressed in the comments. A total of 3,525 comments were gathered from May to October 2020 using an automated data extraction tool.

Table 2. Sentiment Analysis Process

Stage	Action	Description	Tools
1	Data Collection	Retrieving comments from FB posting link and extract it in the form of *.csv file format to be used in the translation stage	• Instant Data Scraper • Microsoft Office Excel
2	Comments Translation	Translating comments using automated machine translation and manual translation and save it in the form of * xlsx file format to be used in the pre-pr0cessing stage	• Google Translate MT • Manual translation by referring to MalayCube online dictionary • Microsoft Office Excel
3	Pre-processing and Sentiment Detection	The process includes: • transformation • tokenization • normalization • filtering Displaying word cloud from the pre-processed data	• Orange Data Mining
4	Sentiment Analysis	Classifying sentiments polarity to each posting (positive/neutral/negative)	• Vader Algorithm in Orange Data Mining

This web scraping technique was done by utilizing a browser extension called Instant Data Scraper. It requires a Facebook user account to be able to retrieve comments from a posting link and then extracted the original comments in the form of *.csv file format as shown in Figure 1. Data scraping is done by placing each posting link into the scrape comment feature. Instant Data Scraper uses artificial intelligence to extract the most relevant data on the pages. In Figure 1, we selected Profile Link, Original Comments, and the number of Likes as our data corpus which comprised 3,525 rows.

Profile Link	Original Comments	Likes
https://www.facebook.com/k	Kesian betul tengok budak ni. He hurt himself so much. How nice kalau ada	206
https://www.facebook.com/A	Anak inilah yang akan tarik dan pimpin tangan mak ayah yg menjaga dia did	362
https://www.facebook.com/k	Kasih Nye ibu tiada penghujung.tiada istilah jemu	51
https://www.facebook.com/s	Kuatnya hati seorg ibu yg menjaga ank syurga ini...dia x mnta utk lahir jd be	80
https://www.facebook.com/c	Aduhai anak syurga..walau bagaimana pun keadaan kamu, semoga kamu si	205
https://www.facebook.com/j	Sbar ye akak dugaan ujian dari allah..kita sama2 doakn anak akak sihat..aka	87
https://www.facebook.com/n	sedeh betul tengok anak 2 macam ini sabar aje dorang melayan kerenah an	20
https://www.facebook.com/r	Ya Allah semoga klurga puan dberi kesabaran kekuatan mnjga anak2 dmuar	21
https://www.facebook.com/n	Bagi saya puan ibu yang kuat dan berkongsi video anak austime dia bkn seb	24

Figure 1. Comments Extracted saved in *.csv Format

3.2 Comments Translation

The second stage is to translate all the extracted comments from Malay to the English language. In this research, the language source of the research data was set to Malay language and Google Translate as the automated Machine Translation (MT). Once the text was translated, the final input data was saved in the Google Spreadsheet data format and converted to *.xlsx format upon downloaded. This dataset is named *dataset_auto*. The comments were also manually translated from Malay to the English language by a university student majoring in Applied Language students whose native language is Malay. The translation was also done with the help of an online Malay dictionary, MalayCube to ensure that the translated comments did not lose their essence after translation. Finally, the translated comments were validated by an academician from Academy of Language Studies. The translated dataset is called *dataset_manual*. Table 3 shows examples of the selected original comments that were translated from Malay to English language *data_auto* and *data_manual* datasets.

Table 3. Automated and Manual Translation to Translate the Comments from Malay to English

Original Comments	**Automated Translation *(data_auto)***	**Manual Translation *(data_manual)***
Anak autisme selalu hendak keluar rumah terutama semasa perintah berkurung	Autistic child always wanted to leave the house especially during this lock down	Autistic child always wanted to go out especially during this lock down
Smua hg nak tjk. Mluat aku	All hg nak tjk. Mluat me	Such a show off. So annoying
Mane bapak die? Tak pernah tengok	Mane father die? Never seen	Where is his father? Never seen him
Ya Allah, semoga kamu segera pulih	Oh God, may you recover soon	Oh God, may you recover soon

For example, the original comment /*Smua hg nak tjk.Mluat aku*/ has been automatically translated to /*All hg nak tjk. Mluat me*/ compared to manually translated /*Such a show off. So annoying*/. The latter translation is more meaningful. While some comments were translated correctly, others were not. Both the automated and manual translations were then used in semantic analysis.

3.3 Pre-processing and Sentiment Detection

In the third stage, sentiment detection was done using a sentiment analysis tool called Orange (Demsar *et al.*, 2013). Orange is an open-source toolkit that offers machine learning, data visualization, and data mining through Python scripting. Both the *dataset_auto* and *dataset_manual* comments were fed into Orange to detect their corresponding sentiments. In this research, the design of the sentiment detection was done using Orange widgets as illustrated in Figure 2. Widgets are visual components in Orange that contained functionalities and they communicate with other widgets by passing objects through the communication channel to perform their specified tasks.

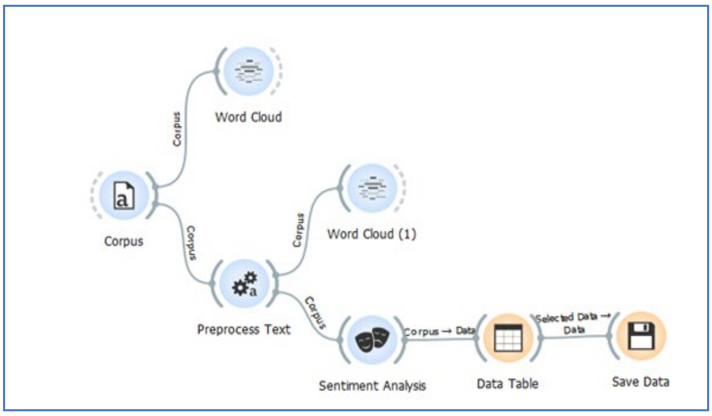

Figure 2. Design of Sentiment Analysis using Orange Widgets

As can be seen in Figure 2, the Corpus widget loads the input data file which is the automated and manually translated English comments. The content of the data file can be visualized using a Word Cloud widget. The words' sizes are presented denoting the occurrence of word frequencies in the dataset. See Figure 3. Here, we can see that the most used word in the comments are /good/, /god/, /hope/, /may/, /patience/, /healthy/, /stay/, /children/ and /always/.

Figure 3. Word Cloud of the Machine Translation English Comments

Before sentiment detection, the input data file needs to be pre-processed using lexicon normalization which was done by Pre-process Text widget. The processes include a) transformation into lowercase, b) tokenization using the regular expression '\w+', c) normalization and d) filtering as shown in Figure 4.

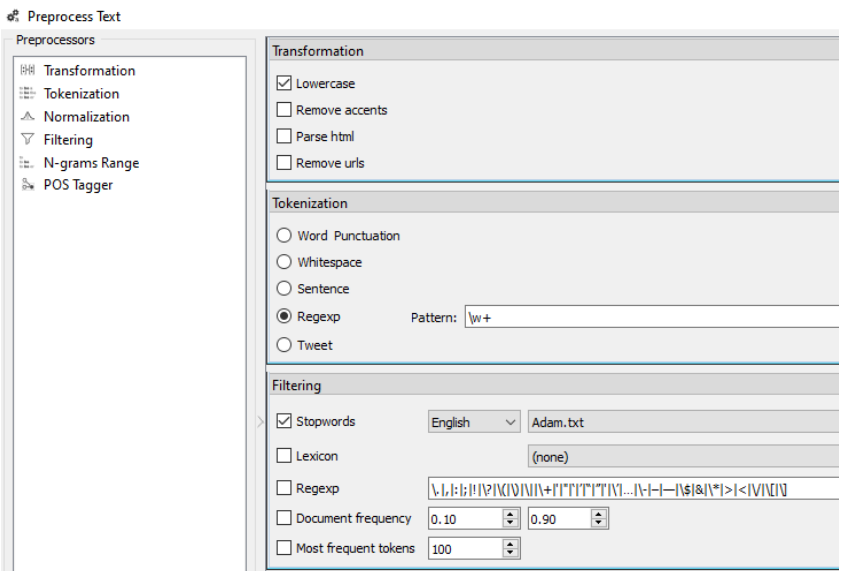

Figure 4. Pre-process Text Settings

The transformation process converted all the comments into lowercase and removed all punctuations. Meanwhile, tokenization split the comments into individuals using word characters [A-Z, a-z, 0-9, _]. Next, all stopwords were removed leaving only meaningful words to be analysed. An example of tokenization and stopword removal is shown in Table 4.

Table 4. Example of Pre-processed Text

Translated comments	Where is his father? Never seen him.
Lowercase	where is his father? never seen him.
Removed punctuations	where is his father never seen him
Tokenization	/where/ /is/ /his/ /father/ /never/ /seen/ /him/
Removed stopwords	/where/ /father/ /never/ /seen/

After tokenization, the normalization was applied to stemming and lemmatization of text using WordNet Lemmatizer. WordNet Lemmatizer implements a cognitive synonym network for tokens (words) based on a large English lexicon (dictionary) database of Natural Language Toolkit (NLTK). The final process in pre-process text was filtering i.e. deleting or saving word choices. Here is a process where the processing of filtering words, and symbols that are not needed in sentiment analysis.

3.4 Sentiment Analysis

In Orange, the sentiment polarity (class sentiment) is classified into positive, negative or neutral using Valence Aware Dictionary and Sentiment Reasoning (VADER) algorithm in the Sentiment Analysis widget in Figure 2. VADER is a lexicon and rule-based sentiment analyzer that used sentiment modules from Natural Language Toolkit (NLTK) documentation located at (http://www.nltk.org/api/nltk.sentiment.html) and multilingual sentiment lexicons of Data Science Lab found at (https://sites.google.com/site/datascienceslab/projects/multilingualsentiment). Each token of the pre-processed comment was given a polarity score of positive, neutral or negative. The total compound score of the comment was then computed by summing the positive, negative and neutral scores and normalized between -1 (most extreme negative) and +1 (most extreme positive). The comment was classified as negative when the total compound value is negative and vice versa. The comment was classified as neutral if it has a total compound value of 0. Finally, the Data Table widget presented the sentiment analysis results in the form of a data table as seen in Figure 5.

1	Profile Link	Original Comments	Translated comments (Google Translate)	Pos	Neg	Neu	Compound
2	https://web.facebook.com/	Anak autisme selalu hendak keluar rumah terutama semasa pkp	Autistic child always wanted to leave the house especially during pkp	0.111	0.166	0.723	-0.3182
3	https://web.facebook.com/	Mane bapak die, tak pernah tengok	Mane father die, never seen	0	0.438	0.562	-0.5994
4	https://web.facebook.com/	Smua hg nk tjk.mluat aku	All hg nak tjk.mluat me	0	0	1	0
5	https://web.facebook.com/	Ya Allah, semoga segera pulih	Oh God, I hope you recover soon	0.427	0	0.573	0.9488

Figure 5. Sentiment Analysis Result in the form of Data Table

The data table consists of the profile link, original comments, translated comments, positive, negative and neutral scores and finally the total compound which is the total score of the sentiment. For example, the translated comment */Oh God, I hope you recover soon/* shows a positive score of 0.427 and a neutral score of 0.573, with a total compound of 0.9488. Since the total compound is approaching +1, the comment was classified as a positive sentiment.

4. Results and Discussion

This research aims to investigate the effect of Google Translate on the analysis of sentiment for social media text on Facebook pages of a caregiver of a person with autism. Since the Malay language is a low-resourced language, the use of MT is convenient and necessary so that sentiment analysis can be done in a high-resource language such as English. However, is MT adequate in achieving the acceptable accuracy of sentiment? Table 5 shows the comparison between the total compound of sentiments for selected comments that are automatically and manually translated, respectively. All comments in the sentiment lexicon were given a polarity score of negative 1, positive 1, and 0 for neutral. If the tokens were non-existence in the sentiment lexicons, they were assigned a polarity score of 0.

Table 5. Comparisons of Total Compound Scores using Automated Google Translate and Manual Translation

No.	Original Comments	Google Translate (*dataset_auto*)	Total Compound	Label	Manual Translation (*dataset_ manual*)	Total Compound	Label
1	Anak autisme selalu hendak keluar rumah terutama semasa pkp	Autistic child always wanted to ***leave the house*** especially during pkp	-0.3182	Negative	Autistic child always wanted to ***go out*** especially during this lock down.	0.1761	Positive
2	***Smua hg*** nak ***tjk***. ***Mluat*** aku	All ***hg*** nak ***tjk***. ***Mluat*** me	0	Neutral	Such a show off. So annoying	-0.4019	Negative
3	***Mane*** **bapak die**? Tak pernah tengok	**Mane** father ***die***? Never seen	-0.5994	Negative	Where is his father? Never seen him.	0	Neutral
4	Ya Allah, semoga segera pulih	Oh God, I hope you recover soon	0.9488	Positive	Oh God, may you recover soon	0.9488	Positive

In the first comment, the automated translated comment; /*Autistic child always wanted to leave the house especially during this lock down*/ shows a negative sentiment with a total compound of -0.3182. The fragments /leave the house/were annotated as having negative sentiment. However, when the comment was manually translated; /*Autistic child always wanted to go out especially during this lock down*/ was detected as a positive sentiment with a total compound of 0.1761. It shows that the automated translation by Google Translate does not coincide with the actual meaning of the comments.

A similar problem occurred for the second comment; it can be seen that the second comment was translated using Google Translate was not entirely accurate and it could not translate some of the words because the original comments used a lot of short forms such as /*smua*/, /*hg*/, /*tjk*/ and /*mluat*/. Therefore, automated translation using Google Translate shows that sentiment analysis resulted in neutral sentiment with a total compound of 0. However, when the comment was manually translated into /*Such a show off. So annoying*/ was detected as a negative sentiment with a total compound of -0.4019. In the future, short forms should be added to the language dictionary as the use of acronyms and short forms are common in social media.

The automated translation in the third comment somehow led to a misleading context. The original comment was /*Mane bapak die, tak pernah tengok*/ was translated using Google Translate into /*Mane father die, never seen*/ scoring -0.5994 value of the total compound. Since the word /die/ meant pass away has a negative sentiment in the sentiment lexicon, the comment was labelled as having negative sentiment. However, when the comment was manually translated into /*Where is his father, never seen him*/ was detected as a neutral sentiment with a total compound of 0. Out of the four comments, only the final comment of /*Ya Allah, semoga segera pulih/* was classified as positive sentiment by the automated and manual translation. The total compound score of 0.9488 was computed based on the positive words of /*God*/ and /*recover*/.

Figure 6 shows the results of the sentiment after translating the 3,525 comments using automated Google Translate. As shown, the majority of the sentiment favoured neutral (2,324 comments) compared to positive (1,021 comments). Hence, the sentiment detected the comments as neutral. Only 180 comments were classified as negative sentiments.

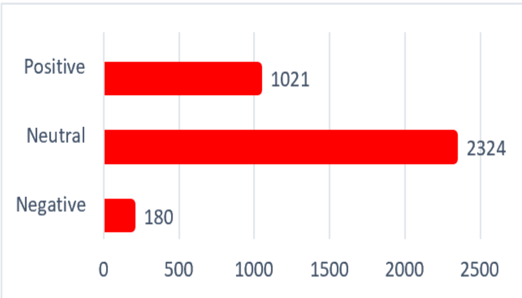

Figure 6. Sentiment Analysis of 3,525 Automated Translated Comments

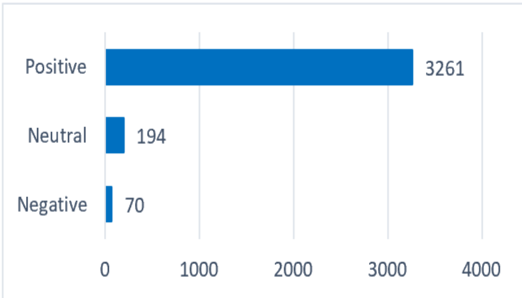

Figure 7. Sentiment Analysis of 3,525 Manually Translated Comments

The results of the sentiment are shown in Figure 7. This serves as the ground truth of the sentiment comparisons. As per shown, majority of the sentiment favoured positive (3,261 comments) compared to neutral (194 comments). This indicates that the Malay-spoken communities are generally positive and encouraging in supporting parents and caretakers of a person with autism.

Table 6 compares the results of the sentiment for all 3,525 Facebook comments using *dataset_auto* and *dataset_manual.* As shown, the majority of the sentiment favoured neutral with 65.9% for Google Translate, while 92.5% of the sentiment favoured positive for manual translation. This indicates that Google Translate is unable to translate the comments from Malay to English accurately since it gives sentiment value based on the translated phrases of the sentence and not the sentence. For that reason, a positive review might be given a neutral sentiment score. It may also be possible because the translation process of Google Translate is not programmed to operate in the same way as human translation, which requires a more advanced cognitive process.

Table 6. Comparison on Sentiment Analysis Result from Automated Google Translate and Manual Translation

Sentiment	**Automated Google Translate Translation**	**Manual Translation**
	Percentage (%)	
Positive	29.0	92.5
Negative	5.10	2.0
Neutral	65.9	5.50

This result indicates that manual translation outperformed automated translation. Although it will not impact entirely the sentiment, however, manual translation helps a lot in doing sentiment analysis (Saif *et al.*, 2016). Therefore, manual translation is important for the accuracy and reliability of the sentiment analysis data.

5. Conclusion and Future Works

Even though Google Translate has shown to be effective in some work of text analyses, it can be counterproductive, particularly for sentiment analysis. In this work, we have shown that the use of Google Translate is appropriate for detecting negative sentiments. However, most positive sentiment comments were listed as neutral comments. Several comments were manually examined to understand why humans incorrectly annotate a sentence automatically translated. Most of the cases were due to bad translation where the sentiment word has either disappeared or its emphasis is changed, or the sentiment of the word is altered. However, in some cases, translations were greatly affected by typos in the Malay language side. In some cases, the automated sentiment analysis system annotates correctly (where manual annotations of translations may fail) because it learns an appropriate model even for mistranslations.

This set of experiments is to systematically examine the impact of translation of Malay language sentiment analysis specifically focusing on comments towards postings regarding the person with autism. The experiments show that the impact of translation at a fine-grain level is high in the level of sentiment or emotion is hugely lost in automated translation where it is fairly retained if translated manually. Besides, Malay language sentiment analysis systems work much better on the manual translation of data rather than on automated translations. This result is consistent with the research done by (Atteveldt *et al.*, 2021; Poncelas *et al.*, 2020). This work is a preliminary investigation of how GoogleTranslate affect the sentiment analysis of social media comments. There is a lot of improvement to be done to this initial work in the future as the following: 1) Further investigation is needed to develop a universal model of sentiment analysis that can be applied to a different type of data. 2) Pre-processing of the comments should be done to correct typos, spelling errors, acronyms, etc. prior to automated translation for fairer comparison to manual translation. 3) The original comments in Malay language can also be annotated with sentiment polarity so that comparison can be done with the manually translated English comments. 4) Another possible extension of this research is to extract social media text from other platforms such Instagram and Twitter.

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8. Author Contribution

Author1 performed fieldwork while Author2 prepared the literature review. Author3 interpreted the results while Author4 oversaw the article writing. Author5 and Author6 wrote the research methodology and abstract respectively.

9. Conflict of Interest

The authors have no conflicts of interest to declare.

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