TelcoSentiment: Sentiment Analysis on Mobile Telecommunication Services

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Abstract

The mobile telecommunication services market in Malaysia has massively grown in the last decade. The competition among the existing and new telecommunication service companies became more intense as they are trying to maintain their existing customers and get new customers at the same time by making a lot of eye-catching promotions and seasonal events. These strategies are often compared by their customers on media social such as Twitter and Facebook. However, it will take a lot of time and effort to capture and review millions of tweets. This study aims to analyse the customer feedback and review on mobile telecommunication services in Malaysia using sentiment analysis approach. We develop a mobile application that analyse user reviews on mobile telecommunication services in Twitter data from Malaysia. The mobile application extracted data from Twitter, preprocessing the tweets in real-time, and visualise the sentiment analysis results using a bar chart, stacked area chart, and word cloud. We found that Naïve Bayes algorithm obtained the highest accuracy with 75.79% for ratio 9:1 and had the most informative features than other algorithms. We assessed the mobile application features using a preliminary evaluation. Many respondents agreed the mobile application is useful in visualising the sentiment analysis results and easy to use. The TelcoSentiment application can be used to suggest the public users in selecting the most preferred mobile telecommunication services. Furthermore, the application will be able to support telecommunication services companies to improve their service performance in the future.

Keywords: sentiment analysis, naïve bayes algorithm, Twitter data, reviews and feedback

I. INTRODUCTION

Telecommunications, especially mobile devices, are necessary for connecting with others from one place to another. These mobile devices are not only used for calling, but also for interacting by text and multimedia messaging and connecting to the internet (Munyanti & Masrom, 2018). Although it was necessary to use this technology in everyday life, due to some situations, the customer might be unhappy with the services provided by the telecommunication service providers (Adebiyi et al., 2016; Chong et al., 2015; Munyanti & Masrom, 2018; Pak & Paroubek, 2010). This happened all over the world because of the competition among the telecommunication service providers that try to maintain their existing customers and to get new customers by making a lot of eye-catching promotions and seasonal events. Therefore, customers tend to express their opinion or feedback of the telecommunication service providers on social networking platforms such as Twitter and Facebook (Adebiyi et al., 2016; Molla et al., 2014; Sungirirai et al., 2017).

Social networking platforms allow public users to post comments daily. One of the main platforms is Twitter that contains huge amounts of user opinions on many issues such as goods, products, activities, organisations, political parties, etc (Lavanya et al., 2016; Omar et al., 2017). Hence, millions of Twitter posts can be used in different fields to collect useful information. One of the important information that can be obtained through the analysis of Twitter data is the opinion and responses towards an issue. It is possible to determine the issue for enhancement and improvement by understanding the public opinions (Adnan et al., 2018; Ji et al., 2015).

The information on public opinions can be collected by following the tweets. However, it will take a lot of time and effort to capture and review millions of tweets (Windasari et al., 2017). Furthermore, the large amount of informal and unstructured data from the people on Twitter makes it difficult for governments or organizations to respond quickly (Omar et al., 2017). Besides, texts can be misleading in opinion or sentiment, which is why people use emoticons or smileys to further clarify their mindset (Tanwani et al., 2018). However, there are several problems to measure user's opinions or sentiments using the Twitter platform.

The first problem to measure opinion is in one situation the opinion can be considered as positive but on the other situation, it also can be considered negative (Aquino et al., 2020; VardanReddy et al., 2019). This type of opinion is difficult to evaluate either positive or negative sentiment. The second problem is most people often used a different way to express their opinions because their comments are inconsistent in terms of positive or negative (Aquino et al., 2020; Pak & Paroubek, 2010). Some comments have both positive and negative feedback which, by evaluating sentences one at a time is somewhat reasonable. For example, the customer tweet the video stream using Maxis is good but the 4G signal is bad. Therefore, we cannot predict the customer feedback towards the Maxis service is positive or negative. Next, sometimes comparison words use the opposite meaning, which is an opinion is difficult to determine whether they provide positive or negative meaning (Iqbal et al., 2015; Rexiline Ragini & Rubesh Anand, 2016; VardanReddy et al., 2019). For example, "Digi service is good at making customer angry". The term "good" normally use in positive responses but in this tweet, it gives a negative response. This indicates the difficulties to identify and analyse the Twitter data using the conventional way.

In Malaysia, several telecommunication companies provide mobile telecommunication services such as Maxis Communication Berhad, Digi Telecommunication Sdn Bhd, Celcom Axiata Berhad, and U Mobile. The entire mobile network has its ongoing investments in network coverage, efficiency, and results, and aims to sustain its technology leadership as the best mobile service provider in the world. One way to sustain is to manage the quality of customer service interaction and engagement by analysing customers' opinions or reviews regarding the network services on the Twitter platform (Fang & Zhan, 2015).

The goal of this research is to analyse and compare user reviews on telecommunication services using the sentiment analysis approach. In this paper, we start by extracting customer's feedback on mobile telecommunication services from the Twitter platform. Then, we develop a mobile application that can analyse user reviews on mobile telecommunication services in Malaysia. In the application, we transform the extracted data from Twitter and visualise the sentiment analysis results in the bar chart, area chart, and word cloud in real-time environment. This will help other people in deciding the preferred mobile telecommunication services. Furthermore, this study can help telecommunication companies to improve their service performance in the future.

II. METHODOLOGY

Sentiment analysis approach mainly has two (2) techniques, which are lexicon-based and machine learning. Machine learning focuses on feature vectors while lexicon-based focuses on building perfect dictionaries. The lexicon-based technique determines the polarity of text data after matching them with any opinion words in the sentiment dictionary (Dattu & Gore, 2015). The opinion words in the sentiment dictionary describe the mode of opinions such as positive, negative, and neutral (Antonakaki et al., 2021). Machine learning technique classifies data using classification techniques such as Naive Bayes, maximum entropy, and support vector machines (Desai & Mehta, 2017). The accuracy of this technique depends on the selection and extraction set of features to detect sentiment (A. & Sonawane, 2016; Vaitheeswaran, 2016).

In this study, we use a hybrid approach that combine both the machine learning and the lexicon-based approaches to improve the sentiment classification performance, and we only focus on the telecommunication service domain (Abu Farha & Magdy, 2021; Devika et al., 2016). We apply a general sentiment analysis workflow that consists of five methods that are data acquisition, preprocessing data, feature extraction, algorithm selection, and algorithm evaluation (Godsay, 2015).

III. DATA ACQUISITION

Data acquisition steps consist of data collection, data extraction, and data cleaning procedures. We collected data for both Malay and English languages. There are two (2) types of corpora, which are datasets of positive and negative sentiments from Twitter and a list of stop words. For the collection of Malay Corpus, we used a dataset from https://github.com/huseinzol05/Malay-Dataset.

The dataset contains positive and negative sentiments from Twitter and a list of stop words of the Malay language. For the collection of English Corpus, we collected datasets from the python library 'nltk'. The python library provides a corpus that contains a collection of positive and negative sentiments from Twitter and contains a list of stop words in the English language.

Datasets retrieve from Twitter contain several attributes such as username, user id, and source, retweet count, tweet text, time, geolocation, and tweet id. This study only requires tweet text that will be used to calculate the sentiment. For each tweet, we extracted the text and store it in JSON format (JavaScript Object Notation) for further processing. We performed data cleaning and normalization to remove twitter noise such as URLs, numbers, punctuations, special characters, and emoticons. We cleaned the Twitter text by correcting typos and slang before applying the next step.

IV. DATA PREPROCESSING

In this step, we performed several processes such as tokenization, stop word removal, lowercase transformation, and emoticons replacement. We used NLTK 3.0 tool Kit with Python in the pre-processing data (Balakrishnan et al., 2020). Tokenization is a process of splitting a stream text into a sequence of individual units called tokens, usually words or phrases. Tokenization can be applied at different levels such as document level, aspect level, and word level.

In this study, we use word-level tokenization using a non-letter character such as @, #, numbers (1,2,3), and URLs. Each tweet is first tokenized separated by space between each word. After the tokenization process, the tokens will be cleaned. In the lowercase transformation process, we converted all upper case into lower case characters and the links, the hashtags, the username, any punctuations, and white spaces will be removed. If the token's character is less than three (3) after the lowercase transformation, the token will be removed. If it is not removed, the token will be stemmed or lemmatized.

Next, we removed stop words in the tweet text. Stop words play a negative role in sentimental analysis, so it is important to be removed. They occur in both negative and positive tweets. We created a list of stop words like he, she, at, on, a, the, etc. Emoticons are frequently used by the user to express their thought. In addition, it is very important in determining sentiment positive and negative. We replaced emoticons with emoticons dictionary to determine their polarity. Table 1 shows an example tweet for data preprocessing.

Table 1Data preprocessing

Before data preprocessing	After data preprocessing
['#FollowFriday', '@France_Inte', '@PKuchly57', '@Milipol_Paris', 'for', 'being', 'top', 'engaged', 'members', 'in', 'my', 'community', 'this', 'week', ':)']	[‘for’, ‘being’, ‘top’, ‘engaged’, ‘member’, ‘community’, ‘this’, ‘week’]

Feature extraction

The selection of useful words from the tweet is called feature extraction. In the feature extraction process, we extracted the important features from the list of tokens by identifying the most frequently mentioned words in the list of tokens. We filtered the stop words in the list of tokens before applying the frequency distribution. Table 2 shows the top 10 most common words for positive and negative datasets, paired with the frequency of the word in the datasets forming a Bag-of-Words (BOW).

Table 2Top 10 important features for positive and negative datasets

Positive	Negative
[('terima', 3694), ('kasih', 3660), ('suka', 2288), ('lihat', 2272), ('selamat', 2082), ('hebat', 1967), ('ketawa', 1906), ('pergi', 1809), ('laku', 1798), ('minggu', 1740)]	[('kerja', 3147), ('sakit', 2638), ('pergi', 2555), ('laku', 2149), ('lihat', 2028), ('sedih', 1688), ('minggu', 1672), ('harap', 1625), ('tidur', 1543), ('rumah', 1432)]

After the frequency distribution process obtained 5000 most common features for both positive and negative datasets, the BOW for both positive and negative datasets is combined, which consists of 7845 features after removing any duplicates on both lists. Figure 1 shows the code segment for feature extraction.

```
pos_words = get_all_words(positive_cleaned_tokens_list, stop_words)
BOW = FreqDist(pos_words)
pos_features = list(BOW.keys())[:5000]

neg_words = get_all_words(negative_cleaned_tokens_list, stop_words)
BOW = FreqDist(neg_words)
neg_features = list(BOW.keys())[:5000]

all_features = pos_features
for feature in neg_features:
    if feature not in all_features:
        all_features.append(feature)
```

Figure 1: Feature extraction

After the features have been extracted, the cleaned tokens were labeled true or false respectively. The token will be labeled true if the token exists in the list of features extracted and the token will be labeled false if it is not found in the list. Figure 2 shows the code segment for the feature labeling process.

```
# function to structure the tokens in model format to be train
def get_tweets_for_model(cleaned_tokens_list, features):
    for tweet_tokens in cleaned_tokens_list:
        yield dict([token, (token in features)] for token in tweet_tokens)
```

Figure 2: Feature labelling

Algorithm selection

After the feature labeling process, we prepared the dataset for testing and training with ratios 70:30 and 90:10. We selected six algorithms to build the classifier for the sentiment analysis due to the availability of the phyton library. The algorithms are Naïve Bayes, Multinomial Naïve Bayes, Bernoulli Naïve Bayes, Logistic Regression, Stochastic Gradient, and AdaBoost. These algorithms can be trained very efficiently and have obtained good results in sentiment analysis (Aljuhani & Alghamdi, 2019; Feng, 2019). We used multiple ratios and six algorithms to find the best accuracy across classifiers. We evaluated the performance of each classification model according to accuracy. The accuracy values were calculated using Eq. (1).

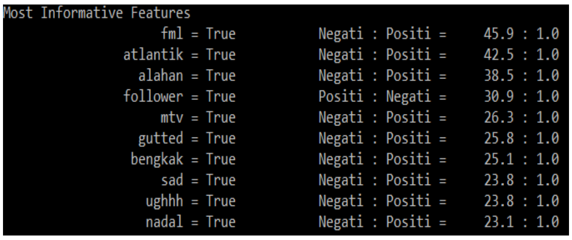
$$\text{Accuracy} = \frac{TP+TN}{(TP+FP+TN+FN)} \quad \text{Eq. (1)}$$

where TP is true positive, TN is true negative, FP is false positive and FN is false negative based on a confusion matrix. Table 3 shows the summary of accuracy results.

Table 3Accuracy results

Test Case	Result	Expected Result
Saya sangat happy	Positive	Positive
Saya sangat sedih	Negative	Negative
Thank you for sending my baggage to CityX and flying me to CityY at the same time. Brilliant service. #thanksGenericAirline	Positive	Positive
I need to die quickly so I can get out of this world	Positive	Negative
I ordered just once from Digi, they screwed up, never used the app again.	Positive	Positive

As own in Table 3, Naïve Bayes algorithm obtained the highest accuracy with 75.79% for ratio 9:1 and the AdaBoost algorithm obtained the lowest accuracy with 67.02% for ratio 9:1. The Naïve Bayes algorithm has the most informative features than other algorithms. Figure 3 shows the list of informative features with negative and positive values for the Naïve Bayes algorithm.



```
Most Informative Features
             fml = True           Negati : Positi =     45.9 : 1.0
        atlantik = True           Negati : Positi =     42.5 : 1.0
          alahan = True           Negati : Positi =     38.5 : 1.0
        follower = True           Positi : Negati =     30.9 : 1.0
             mtv = True           Negati : Positi =     26.3 : 1.0
          gutted = True           Negati : Positi =     25.8 : 1.0
         bengkak = True           Negati : Positi =     25.1 : 1.0
             sad = True           Negati : Positi =     23.8 : 1.0
           ughhh = True           Negati : Positi =     23.8 : 1.0
           nadal = True           Negati : Positi =     23.1 : 1.0
```

Figure 3: Informative features

Algorithm evaluation

Naïve Bayes algorithm is a classification technique for predictive modeling that assumes the presence of a particular feature in a class is unrelated to the presence of other features. It is a simple classifier that able to handle both continuous and discrete data. The Naïve Bayes is a fast processing algorithm and suitable to make a real-time prediction. We validate the Naïve Bayes algorithm that obtained the highest accuracy classifier by performing test case evaluation. We tested the Naïve Bayes algorithm with five test cases as shown in Table 4. Out of 5 test cases, only 1 test case is failed due to the combination of positive and negative sentiment in the text. Therefore, we chose the Naïve Bayes algorithm as the main classifier for this study.

Table 4 Algorithm evaluation

Algorithm	**Ratio**	
	7:3	**9:1**
Naïve Bayes	75.13%	**75.79%**
Multinomial Naïve Bayes	72.56%	72.87%
Bernoulli Naïve Bayes	72.67%	73.04%
Logistic Regression	72.65%	73.00%
Stochastic Gradient	72.74%	72.96%
AdaBoost	66.36%	67.02%

V. RESULTS

In this section, we present the development of a mobile application for sentiment analysis on mobile telecommunication services in Malaysia. We also present the results for the application implementation on mobile telecommunication services in Malaysia.

TelcoSentiment application architecture

We developed a sentiment analysis application (TelcoSentiment) for analysing user reviews on mobile telecommunication services in Malaysia. Figure 4 shows the structure and components in the application system architecture. There are three main components: (1) Application, (2) Local files and (3) Back end. First, the user will input the name of the mobile telecommunication services provider in the application. Next, the application will process the input using a sentiment classifier that extracts data from the Twitter platform through the Internet. Then, the application will pre-process the data by calculating the score for each sentiment and display the results in a form of visualisation to the user.

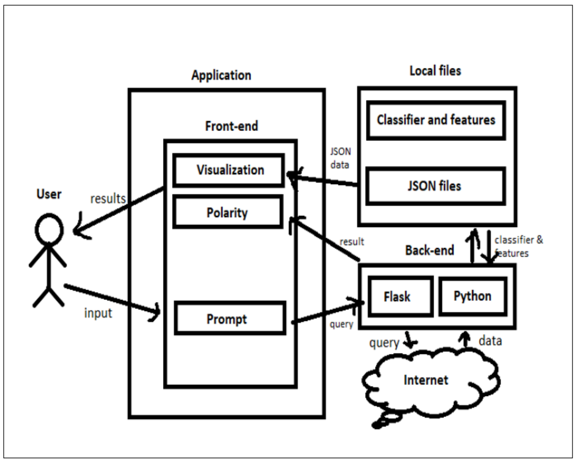


Figure 4: Sentiment analysis application architecture

Figure 5 illustrates the flow chart of the TelcoSentiment application. In the beginning, the user can either pick to recollect data, view stacked area chart or bar chart, view word cloud, and classify query. If the user pick recollect data, the application will start scraping data from Google and Twitter. The data from Twitter will be transformed to word cloud and data for stacked bar chart while the data from google will be transformed to data for stacked area chart. The generated data are then stored in local server in JSON format.

TelcoSentiment application flow chart

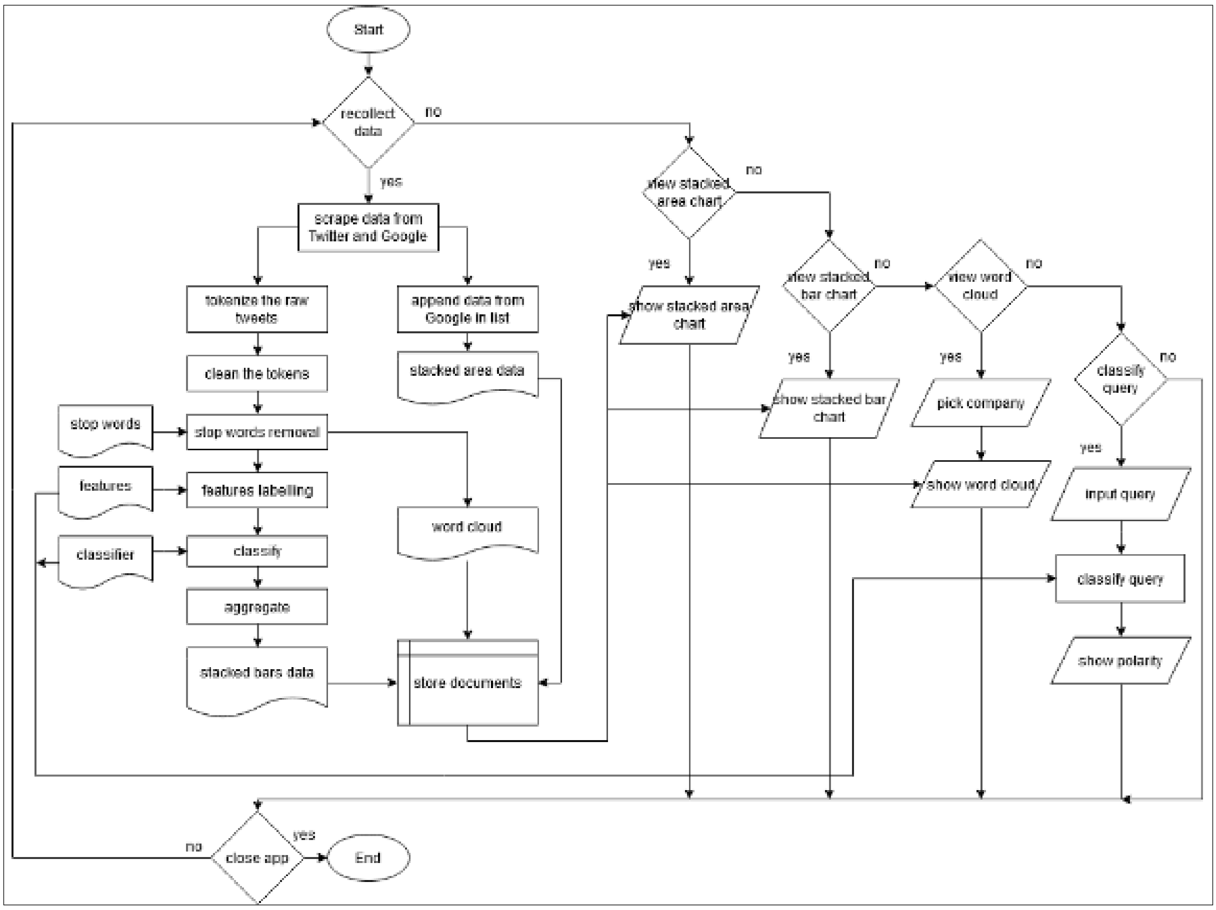


Figure 5: Flowchart for TelcoSentiment application

TelcoSentiment application

The TelcoSentiment mobile application consists of four (5) tabs where each tab has its unique feature. The features are query classifier, recollect data, word cloud, bar chart visualization, and trend line visualization. Figure 6 shows the design of the user interfaces for each feature.

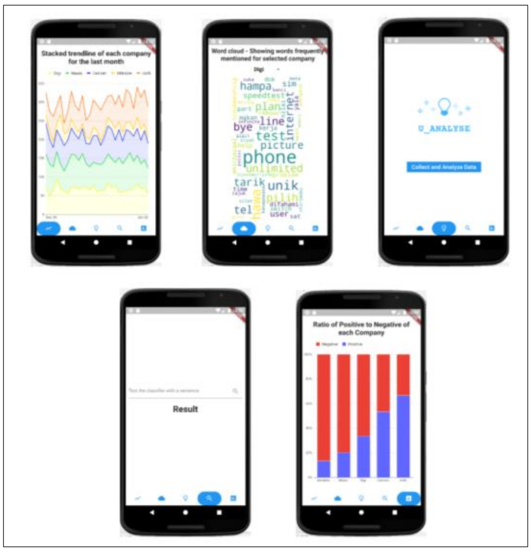


Figure 6: TelcoSentiment application features

To test and evaluate the application features, we collected scraped tweets from Malaysia based on queries of Digi, Celcom, Maxis, UMobile, and Unifi. We applied the five methods of sentiment analysis approach to the raw tweets that are data acquisition, data preprocessing, feature extraction, and classifier implementation. After each tweet is polarized, the data are aggregated by positive and negative for each mobile telecommunication service.

The TelcoSentiment application displayed the sentiment results analysis in a form of bar chart visualization that shows the ratio of positive and negative sentiment for each company. Figure 7 shows the bar chart visualization from the mobile application.

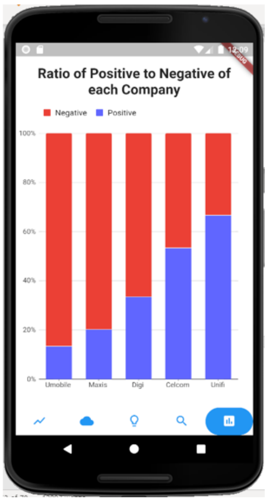


Figure 7: Sentiment analysis result

As can be seen in Figure 7, Unifi and Celcom received more than 50% positive sentiment compared to others. Digi, Maxis, and Umobile received less than 50% positive sentiment. This indicates that many users like to post positive reviews for Unifi and Celcom due to the high-quality services provided to the public users. Umobile received the highest negative sentiment with more than 80%. It seems that most users posted negative reviews for Umobile because of the low quality of services.

In this study, we also test another visualisation feature that able to show how frequently does each company appears in the Google search engine for the past month. We recollected the scraped Tweets from Malaysia based on queries of Digi, Celcom, Maxis, UMobile, and Unifi using the Recollect and Analyse feature to get the most recent tweets. The application displayed the results analysis in a form of stacked area chart. Figure 8 shows the search trend of telecommunication company for the past month.

Figure 8: Search trendline for telecommunication service company

The trendline results in Figure 8 show the uptrend in the Unifi searching in the Google search engine with more than 300 searches. UMobile is the less frequently mentioned in the past month compared to other companies. This indicates that UMobile is the least popular mobile telecommunication company in the past month. The results from this feature able to provide information on which telecommunication company is popular in the last month.

The word cloud feature allows users to get the relevant terms that are described with a particular telecommunication company. We evaluated this feature with 'Digi'. The

TelcoSentiment application generated a word cloud that shows the frequency of the word mentioned with 'Digi' in Figure 9. We can see the biggest word in Figure 9 is the word 'phone', which indicates the highest frequency of the word mentioned with Digi. We also can see the word 'hampa' (disappointing) was frequently mentioned with Digi. This could indicate that most Digi users are disappointed with Digi's services.

Figure 9: Word cloud result for 'Digi'.

TelcoSentiment application preliminary evaluation

This section describes the preliminary evaluation of our sentiment application. We designed a short questionnaire that can be used to measure three elements of usability of users. The three elements are usefulness, ease of use and satisfaction. The questionnaire consists of 10 questions to measure usability of the sentiment application. These questions were adapted from System Usability Scale (SUS) questionnaire, which is one of the most frequently used questionnaires to measure usability of system. Table 5 shows the questions in the questionnaire.

Table 5

***Questions for usability evaluation*.**

No.	Question
Q1	I think that I would like to use this mobile application frequently
Q2	I found this mobile application unecessarily complex
Q3	I thought this mobile application was easy to use.
Q4	I think that I would need the support of a technical person to be able to use this mobile application.
Q5	I found the various functions in this mobile application were well integrated.
Q6	I thought there was too much inconsistency in this mobile application
Q7	I would image that most people would learn to use this mobile application very quickly.
Q8	I found this mobile application very cumbersome to use.
Q9	I felt very confident using this mobile application.
Q10	I needed to learn a lot of things before I could get going with this mobile application.

The usability responses shown in Figure 10 were highly positive. Overall, the result of the preliminary evaluation indicates the majority of participants responded that they agreed or strongly agreed the TelcoSentiment application was perceived to be highly useful, easy to use and highly satisfied by the participants.

Most participants agreed that the application is useful in visualising the sentiment analysis for telecommunication services. 70% of the participants agreed that the application functions are well integrated. This indicates that the mobile application helps users in deciding the preferred mobile telecommunication services based on the sentiment analysis results. Majority of participants agreed that the application is easy to use. 70% of participants agreed that the sentiment application is easy to learn and they felt confident to use the application. This indicates that the sentiment application has easy to use functions with straightforward graphical user interfaces.

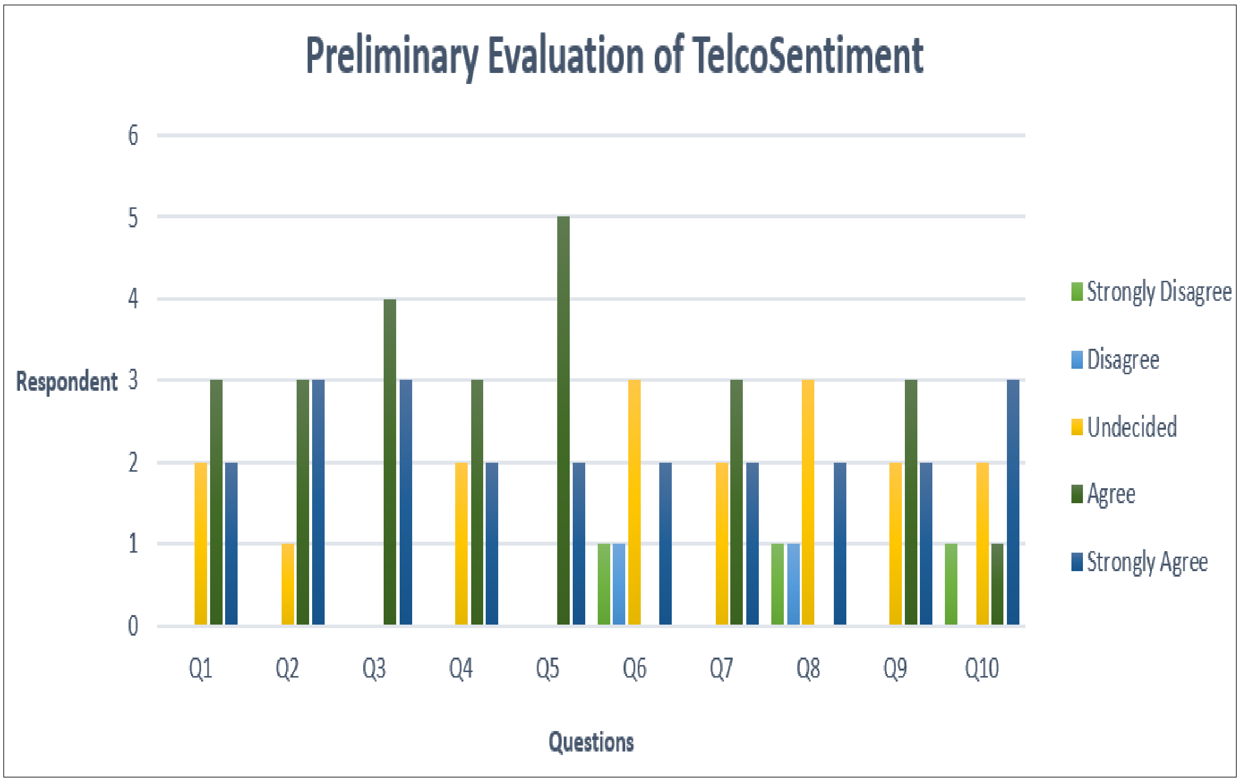


Figure 10. Usability responses

VI. DISCUSSION

This study set out to determine the user feedback and review about mobile telecommunication services. We developed a sentiment analysis mobile application (TelcoSentiment) for analysing user reviews on mobile telecommunication services in Malaysia. We use the sentiment analysis approach, which contains five methods: data acquisition, data preprocessing, feature extraction, algorithm selection, and evaluation. We collected scraped tweets from Malaysia based on queries of Digi, Celcom, Maxis, UMobile, and Unifi. After the raw tweets were processed and cleaned, we applied the Naïve Bayes algorithm as our main classifier to classify the positive and negative sentiment. We visualised the sentiment results analysis in three kinds of visualisation features in the mobile application namely, bar chart, stacked trendline, and word cloud.

TelcoSentiment application provides a platform for public users to find out user feedback and review on the telecommunication services. In addition, the application will allow users to compare the ratio of positive and negative sentiments for each telecommunication company based on the recent reviews because the application collects tweet data in a real-time environment. The TelcoSentiment application is unique because the Tweet data is tailored for telecommunication companies in Malaysia. It appears that the TelcoSentiment application has high potential to be used by most users from Malaysia and would substantially helping the telecommunication companies to improve their service performance in the future.

We evaluate the TelcoSentiment application features with seven participants in a preliminary evaluation session via Google Meet and Google Forms. Overall, the majority of the respondents reacted positively to this mobile application, and they agreed that the features are effective in visualising the sentiment analysis results based on the review of telecommunication services. In addition, most of the respondents agreed that the application is easy to use, and the features are well integrated.

VII. CONCLUSION

This study discussed the detailed design and development of sentiment analysis mobile application using naïve bayes technique that aims to help users in choosing the most suitable and preferred mobile telecommunication services. The sentiment analysis application engine consists of algorithms for parsing, tokenizing, feature extraction, and classifier execution. In the feature extraction process, we extracted the important features from the list of tokens by identifying the most frequently mentioned words in the list of tokens. For classifier execution, we use the Naïve Bayes algorithm to consistently classify the positive and negative sentiment in the real-time prediction.

The preliminary evaluation has shown that the TelcoSentiment application is useful in terms of visualising the sentiment analysis results and easy to use by a small number of users. Nevertheless, further evaluation on the application effectiveness and efficiency can be explored together with the impact towards improving the performance of telecommunication services. We hope that the TelcoSentiment application will be able to give benefit not only public users but also telecommunication companies in Malaysia.

VIII. ACKNOWLEDGEMENT

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