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Customer Sentiment Classification in Mobile Banking: Analyzing Feedback Through Sentiment Analysis

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ABSTRACT

Innovation and technology have subsequently transformed banking industry's way of delivering products and services to their customer. Mobile banking is an effective way of performing transaction as it can be performed anywhere and anytime. The evolution of banking experience is important to fulfil customers' need and demand especially in highly competitive banking industry. Through mobile banking application, customer can express their satisfaction and dissatisfaction directly on the application store platform. The fulfilment of customer's satisfaction is important to avoid customer attrition. This research focused on customer feedbacks towards six mobile banking application in Malaysia which is Maybank, Commerce International Merchant Bankers (CIMB), Public Bank, Hong Leong Bank, Rashid Hussein Bank (RHB) and AmBank. This research aims to identify keywords related to customer feedback towards mobile banking, classify the sentiment and evaluate the accuracy performance by using supervised machine learning algorithm of support vector machine (SVM) and naïve Bayes (NB). The result shows that linear SVM is the best model with the highest value in all accuracy, precision, recall, including F1-score with value 97.17%, 97.21%, 97.17% and 97.18% respectively. With this high accuracy value, this model would have better performance in analyzing the classification of customer feedback in mobile banking application.

1. INTRODUCTION

A customer can be defined as a receiver, consumer or buyer of a company's products and services. Opinions and feedbacks given by customer after experiencing services and products is beneficial to accurately regulate business operation that fits the customers' need. In this era of internet and digital world, there are numbers of knowledge and information readily available at the end of your fingertips. The advancement of technology forces banking industry to move towards using mobile banking. The transformation on banking transaction from paper-based to an electronic payment is an example to see how banking industry has evolved. In banking industry, the prospect of revenue growth and operational efficiency is essential for all business in order to stay relevant and survive in the industry. High competition between banks is one of the factors that leads to this migration.

Nowadays, customer prefer to use mobile phone in doing all activities including on getting services. One of the reasons is due to unlimited access on owning a mobile phone regardless of social status. Internet network services that readily available at a low cost has subsequently contribute to the rise of mobile phone users. This is where the needs on having mobile banking application emerged. Mobile banking defines as a capability on performing financial transaction via mobile device [1]. Thus, customers can have access to their respective bank account and perform the transaction anytime and anywhere without the need on going to the physical bank.

In Malaysia, there are numbers of mobile banking application available namely Maybank My, Commerce International Merchant Bankers (CIMB) Clicks, PB Engage, Rashid Hussein Bank (RHB) Now and many more. With wide range of feedbacks and reviews available, study on sentiment analysis is important for a company to classify those comments for products and services improvement. In this current competitive world, building a strong relationship with the customer has become an important strategy. Banks must battle to provide the best in customer satisfaction by introducing innovative strategies [2], [3] stated that a business spends a huge amount of money and time on brand monitoring and gathering real-time customer feedback. Dissatisfaction on services provided would affect business reputation and lead to customer attrition, thus, consequently impact the business's revenue. Customer attrition is an important issue faced not just in banking industry but also in insurance company, mobile service provider and many more [4]. Prompt action should be taken to retain existing customer and attract potential customer to perform business with the bank. An implementation of analytics is undeniably important for business if it can be rationally applied and identified in monitoring the customer behaviour towards business operation [5].

The aim of this research is to classify customers' feedback made on mobile banking application by using ML techniques. Three objectives are defined which firstly, is to classify the customer's feedback based on sentiment polarity score. Secondly to identify keywords related with customer's feedback towards mobile banking experience and lastly to evaluate the performance of sentiment analysis classifiers by using performance matrix. For this research, classification of large scale customer feedback towards mobile banking application in Malaysia is focused. The data of customer's feedback towards mobile application will be extracted based on six (6) banking institutions in Malaysia based on the review posted via their official mobile banking application platform. ML algorithms of naïve Bayes (NB) and support vector machine (SVM) are used to predict the accuracy of sentiment classifications. For NB, the kernel used is multinomial naïve Bayes (MNB) and bernoulli naïve Bayes (BNB) while for SVM, the kernel used is linear support vector machine (LSVM). The findings of this research are significant as it provides insight for banking institution on users' reaction towards their mobile banking applications to fulfil the customer experience. According to [2], it is vital for banks to collect customer feedback from various banking services. With the results from this research, an improvement could be made to come up with an application that suits customer's needs by enhancing the related aspects to compete with other mobile application in banking industry. Other than that, this research also useful in providing information for public user on the performance of mobile banking application available. A view on service provided through this mobile banking could be a reason for a banking industry to attract a customer to perform business with them. Furthermore, a good mobile banking platform would be a factor to retain customer in savings and performed financial transaction thus subsequently will gain a strong bond between banking institution and customer.

Research on sentiment analysis of customer's feedback and review has been widely covered on various field by researchers in the past. Hasan *et al.* [6] conducted a ML based sentiment analysis focusing on user tweets about politics in Pakistan. The tweets were written in Urdu and translated to English. In this research, the accuracy of NB and SVM is compared. The result shows word sequence disambiguation (W-WSD) had the highest accuracy in NB classifier with the percentage of 79.00%, followed by 76.00% and 54.75% for TextBlob and SentiWordNet. In SVM, TextBlob had the highest accuracy in comparison with W-WSD and SentiWordNet with the percentage of 62.67%, 62.33% and 53.33% respectively.

Lien [7] analysed review from bank customers in Norway. The author defined the polarity proportion based on 1-5 stars rating review given by the bank customers. The reviews are gathered from three sources which are the bank's review sites, social media and discussion forums. ML algorithm of gaussian naïve Bayes (GNB), LSVM and maximum entropy (ME) in used where the models is conducted with 5-fold cross validation. The result shows that ME result in highest accuracy. Rana and Singh [8] used LSVM and NB to identify film user reviews and detect opinion. The accuracy of algorithm is process on each movie genre namely action, adventure, drama and romantic where from the experiment, LSVM shows a higher accuracy compared to NB in all genres mention with the highest accuracy in drama type of movie. Furthermore, Ayo *et al.* [9] used RapidMiner to combine tweets and comments on Facebook from five major banks in Nigeria. The result is divided into two parts which is by using sentiment analysis and clustering analysis. The sentiment analysis was made to compare the most negative value (MNV) and most positive value (MPV) on tweets and comments between banks. Kumar and Dabas [10] proposed social media complaint workflow automation tool that use sentiment analysis on social media to actively respond on complaints. Based on the study, three variants of NB classified are used consist of MNB, BNB, GNB and SVM. The classifiers are implemented to see the performance against social media post of HDFC Bank India. The results show that approximately 83% and 75% of accuracy achieved by MNB cassifier in the analysis of sentiment classification and department classification respectively. Altrabsheh *et al.* [11] analysed a real-time student feedback with sentiment analysis. Data regarding student's feedback, opinion and feeling on lecture session were collected. The technique used in the experiments are NB, complement naïve Bayes (CNB), ME and three types of SVM kernels namely linear, radial basis and polynomial. The result shows that SVM has high accuracy in precision, recall and F-score. Shi and Li [12] used sentiment analysis model for online hotel reviews. The study used SVM technique for the sentiment classification with unigram feature consist of information on frequency and term-frequency inverse document frequency (TF-IDF). The result shows that TF-IDF is more efficient. Go *et al.* [13] used ML techniques to correctly categorize Twitter post as either positive or negative. The supervised classifiers used are NB, ME and SVM where NB have the highest result of 84.2% compared to the other two classifiers.

From the literature, SVM and NB are the common techniques used in research of sentiment analysis. This section summarizes the frequently used techniques for sentiment analysis of customer feedback. With this motivation, this paper has proposed to use NB and SVM method and compare the results to find the best model for sentiment analysis of customer feedback in mobile banking application.

2. RESEARCH METHOD

Based on cross-industry standard process for data mining (CRISP-DM) method [14]. This research proposed a research model as shown in Figure 1. The processes involve are data collection, data pre-processing, model development, model evaluation and lastly results deployment.

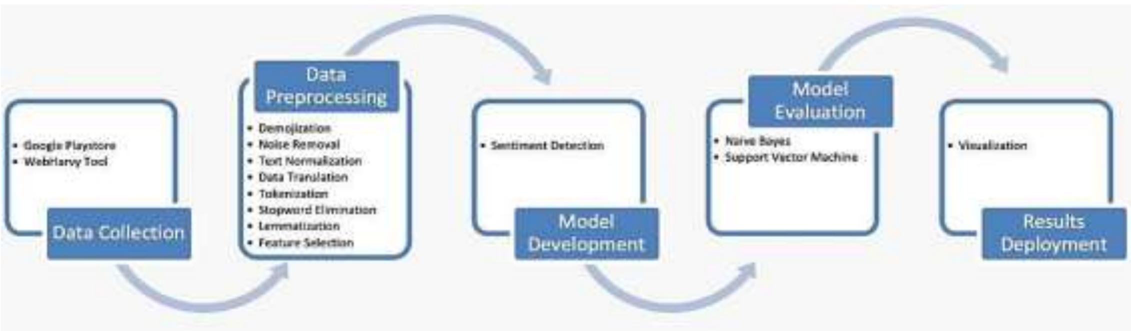

Figure 1. Proposed model

In the first process, data of customer's feedback towards mobile banking application will be collected from Google Playstore for Maybank, CIMB, Public Bank, RHB Bank, Hong Leong Bank and AM Bank. The reviews were extracted on 7th March 2020 focusing on first 100 pages in user review section. The author of the reviews are bank customers and the reviews were written in mix languages consist of Malay, Chinese and English language. Three attributes are used namely 'Rating' which contains the rate given by user, 'Descriptions' which contains the user's review on the application and 'Bank Type' which is type of bank for each review.

Pre-processing is a method to improve sentiment analysis by cleaning the data from undesirable elements to increase the accurateness thus lessen the existence of error in processing the outcomes. The user reviews consist of great amount of vague information that need to be eliminated. Shekhawat [15] stated that data cleaning process is important to compute the sentiment score so that machine will easily understand the text. Pre-processing involves demojization of transforming emojis to the textual equivalent form [16], [17], noise removal for text normalization [18]. The review captured is in the form of multiple languages such as Malay, Chinese and English. Since Malaysia is a multi-racial country, thus it is normal for the people to give reviews and feedbacks in their preferred language. For this research, translation is applied to translate the languages into English language. Desai and Narvekar [19] stated that, spelling errors is produced unintentionally due to human errors. The spelling corrections process is important to avoid the system from ignoring important words in the reviews. Tokenization is used to divide the text of documents into separate series of words or sequence of tokens [20], [21]. Stopword elimination is implemented to enhance the system performance despite reducing the number of texts [22], [23]. Lemmatization is the technique to reduce related word to common root word form [8], [22]. The example of lemmatization can be seen in a word variation like "feature", "featuring", "features" and "featured" where these words is belonged to root word "feature".

Feature in language processing refers to the textual data that is converted to numeric vector [24]. In data extraction phase, a bag of word needs to be converted in vector model. According to [18] there are three ways for converting terms into vector namely term frequency, term occurrences and TF-IDF. TF-IDF is a weighing factor that can be used to replace binary and word count representation [25]. Conversion of term to vector produce a lower weightage to irrelevant terms while a higher weightage to the relevant terms with vector value of 0 and 1 respectively. In this research, TF-IDF is used as a weighting scheme to create the word vector [26]–[28].

In model development, clean dataset is used to detect the sentiment of customers' review either positive, neutral or negative sentiment. To provide valuable insight from the emotion and opinion stated, Textblob sentiment analyser will be used to determine the polarity and subjectivity score of each review. The polarity score [29] is determined by assigning a score from -1 to 1 based on the words used where a negative score represents a negative statement, a positive score represents positive statement while zero value indicates a neutral statement. On the other hand, subjectivity score is determined to know either the context of the review is in subjective meaning or objective meaning. It is based on range value of 0 to 1, the closer the score to 1 the more subjective the text is.The score that are more than 0 will be classified as positive sentiment, score which are less that 0 is negative sentiment and equal to zero as neutral sentiment. The polarity score is determined based on reviews given by user under "Descriptions" column. According to [30], in a survey made on user review posted in Google Play Store, user review act as an important source of knowledge for developers as it provides wide information in terms of issues and improvement can be made on the application. Noei [31] stated among the important pieces of information hidden in the user reviews are user's expectations and concerns, feature requests, bug reports, and guidelines planning for a future release.

Sentiment analysis consist of three polarity classes, which are positive, negative and neutral The sentiment polarity is set based on user review instead of rating score due to unclear definition and inconsistent personal interpretation of star rating. The star rating score given might be differ from the reviews stated. As the polarity score has been determined, the sentiment datasets are then evaluated. The evaluation will be based on the concept of confusion matrix. The classifiers used are SVM and NB. For NB, the kernel used is MNB and also BNB while for SVM, the kernel used is LSVM. The polarity of sentiment classification is in three-class classification, the confusion matrix is extended as shown in Table 1.

Table 1. Confusion matrix of polarity sentiment classification

	Predicted Positive	Predicted Neutral	Predicted Negative
Actual Positive	True Positive (T_{p_p})	False Neutral (F_{N_p})	False Negative (F_{n_P})
Actual Neutral	False Positive (F_{p_N})	True Neutral (T_{N_N})	False Negative (F_{n_N})
Actual Negative	False Positive (F_{p_n})	False Neutral (F_{N_n})	True Negative (T_{n_n})

3. RESULTS AND DISCUSSION

This section discusses on the results and findings of the experiments. 46% of the reviews belongs to CIMB banking application with the number of 22,903 reviews, followed by 34% (17,028 reviews) from Maybank application, 9% (4,752 reviews) from Hong Leong Bank application, 5% (2,618 reviews) from AM Bank application, 4% (1,787 reviews) and 2% (1,082 reviews) for RHB Bank and Public Bank applications respectively.As shown in Figure 2, even though the number of reviews is top by CIMB application, we can see that most of the review given by user was 1-star rating. On the other hand, for Maybank application most of the reviews given was 5-star rating. The star rating refers to a score that represents the user's impression when using certain product and services. The number of stars given can be describe as their level of satisfaction on using these mobile banking applications.

Most of score is between 0 to 1 meaning the sentiment will be more on positive sentiment compared to neutral and negative sentiment. Table 2 illustrates positive sentiment has the highest score of 27,718. Sentiment count made by each mobile banking applications shows a higher positive sentiment especially in Maybank, CIMB and Hong Leong Bank applications with the positive value that almost twice the value of negative and neutral sentiments.

Wordcloud is used to find a keyword related with mobile banking applications. The word clouds consist of the list of words related to negative and positive sentiment classifications. Figure 3 shows the list of words related to positive sentiment where we can see that the highest frequency of words generated were "good", "new", "easy", and "problem". From this list, it can be assumed that user feel satisfied when the application is updated, user friendly and able to solve their problem when doing transactions. On the other hand, Figure 4 shows the list of words related to negative sentiment where we can see that the highest frequency of words generated are "stupid", "bad", "slow", "worst" and "useless". From the list generated, it can be assumed that the user is having an issue when trying to log in to their account. It is also can be said that the negative sentiments are closely related to the performance of the application in performing the online transaction.

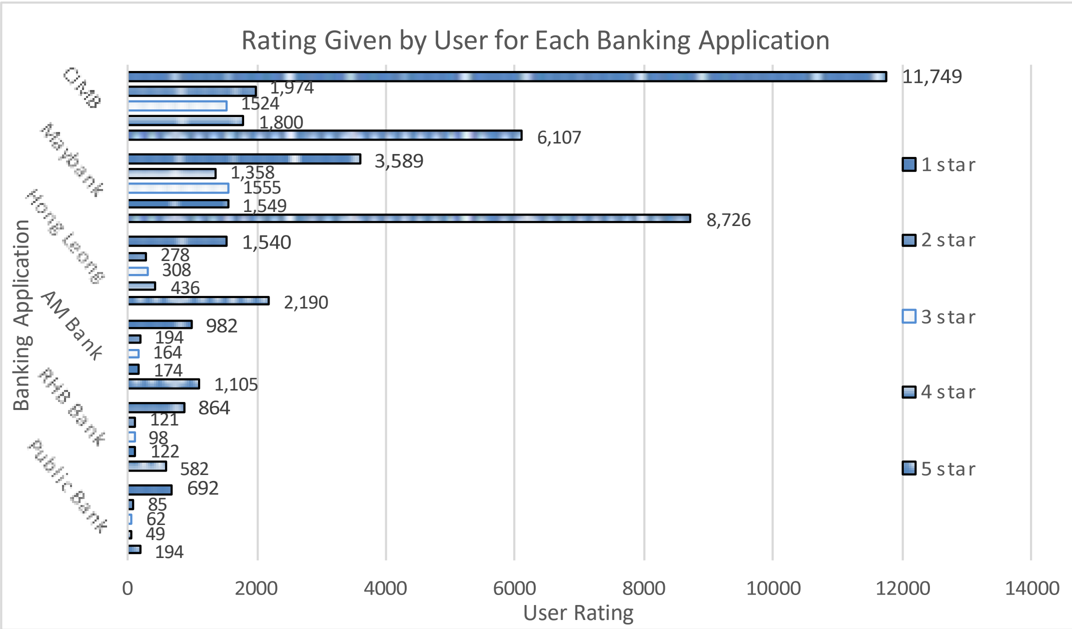

Figure 2. Rating given by user for each banking application

Table 2**.** Sentiments by bank type

Bank Type	Sentiments Positive	Neutral	Negative	Counts
CIMB	10,568	5,945	6,390	22,903
Maybank	11,488	3,659	1,881	17,028
Hong Leong Bank	2,860	999	893	4,752
AM Bank	1,399	582	637	2,618
RHB Bank	941	362	484	1,787
Public Bank	462	302	318	1,082

Figure 3. Positive word cloud

Figure 4. Negative word cloud

In this section, the accuracy, precision, recall and F1 score is compared. Table 3 shows the confusion matrix for MNB. It shows that out of 5,017 total reviews there are 846 negative sentiments predicted correctly, making the result of accuracy for MNB classifier become 83.16%. Figure 5 shows the result of precision, recall and F-measure in each sentiment classes by using weighted average. Negative and neutral has the highest recall value. Meaning it has a higher negative and neutral sentiment that were correctly predicted. On the hand for positive sentiment, it shows a high precision where the value is defined as the proportion of texts that are correctly predicted over total prediction of positive texts.

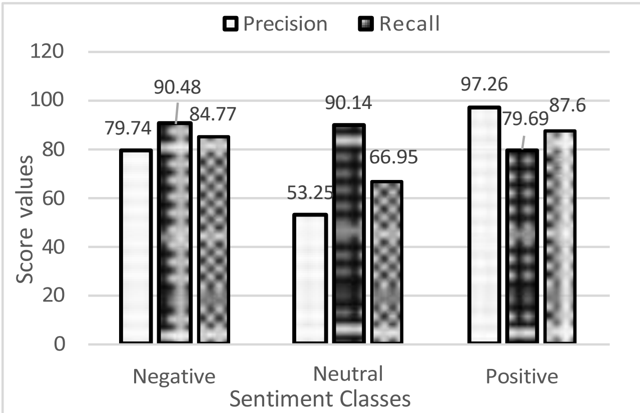

Figure 5. Precision, recall and F1 score values for MNB classifier

Table 3. Confusion matrix for MNB classifier

		Predicted		
		Negative	Neutral	Positive
Actual	Negative	846	41	48
	Neutral	41	631	28
	Positive	174	513	2,695

Table 4 shows the confusion matrix for BNB, the confusion matrix shows that out of 5,017 total reviews there are 729 negative sentiments predicted correctly, 947 neutral sentiments predicted correctly, and 2,577 positive sentiments has been predicted correctly. BNB shows the accuracy of 84.77% while for precision, recall and F1-score result, it is as per shown in Figure 6. Thus, for BNB it also has a higher negative and neutral sentiment that were correctly predicted over the actual amount. Positive sentiment shows highest precision percentage.

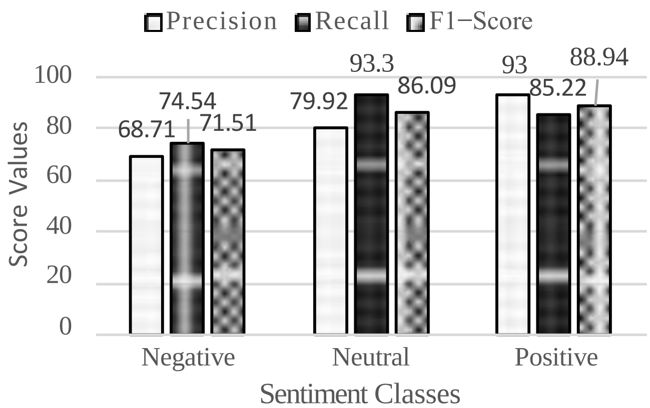

Figure 6. Precision, recall and F1 score values for BNB classifier

Table 4. Confusion matrix for BNB classifier

		Predicted		
		Negative	Neutral	Positive
Actual	Negative	729	71	178
	Neutral	52	947	16
	Positive	280	167	2,577

Furthermore, the confusion matrix for LSVM is shown in Table 5, the confusion matrix shows that out of 5,017 total reviews there are 988 negative sentiment predicted correctly, 1,164 neutral sentiment predicted correctly, and 2,723 positive predicted correctly making accuracy of 97.17% for LSVM classifier. Figure 7 shows the result of precision, recall and F-measure in each sentiment classes. LSVM shows a slightly different result compared to both NB classifier where negative sentiment has a high recall value. On the other hand, neutral and positive sentiment shows a high precision value with the percentage of 98.23% and 98.27% respectively.The result shows that LSVM is the best technique with the highest value in all accuracy, precision, recall, including the F1-score to predict sentiment of customer feedback in mobile banking application. For the result obtained above, the positive and negative word clouds indicate the most frequent words that appear in the feedbacks given by customer.

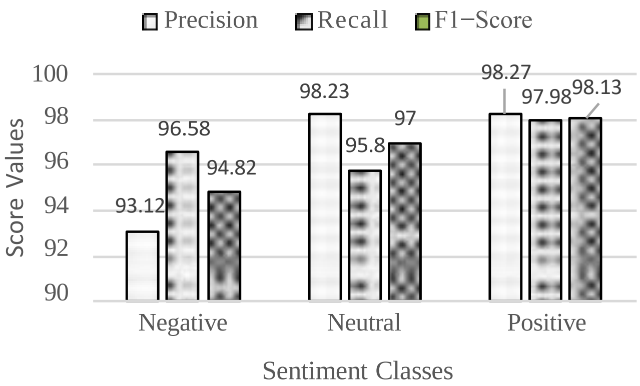

Figure 7. Precision, recall and F1 score values for LSVM classifier

Table 5. Confusion matrix for LSVM classifier

		Predicted		
		Negative	Neutral	Positive
Actual	Negative	988	9	26
	Neutral	29	1,164	22
	Positive	44	12	2,723

4. CONCLUSION

This research has potential to be improved in sentiment analysis study. In order to get more valuable information in mobile banking application review, some of the features may be implemented to get more comprehensive solution in determining the sentiments of user review. As the current research is considering only the reviews given by user, hybrid study by analysing the sentiment behind both user review and rating score given can be done by using mean of the stared rating and numeric rating generated in polarity score. This to provide valuable insight from the emotion and opinion written by user. Future work should evaluate the performance by using deep learning models such as convolutional neural network (CNN), recurrent neural network (RNN) and long short term memory (LSTM). Deep learning model is worth to explore as it provides deeper analysis of sentiment and would have more accurate sentiment detection.

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