Sentiment Analysis on Acceptance of New Normal in COVID-19 Pandemic using Naïve Bayes Algorithm

Siti Hajar Aishah Samsudin[1], Norlina Mohd Sabri[2], Norulhidayah Isa[3], Ummu Fatihah Mohd Bahrin[4]
Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA Cawangan Terengganu
Kampus Kuala Terengganu, 21080 Kuala Terengganu, Malaysia

***Abstract*—The COVID-19 pandemic has such a significant impact and causes difficulties in many aspects that the new normal rules should be implemented to reduce the effects. New normal rules have been implemented by governments worldwide to break the virus chain and stop its transmission among the society. Even if the COVID-19 outbreak is under control, governments still need to know whether society could adapt and adjust to their new daily lifestyles. Many precautions still must be addressed as the transition to endemic status does not mean that COVID-19 will naturally eventually disappear. The World Health Organization also has warned that it is too early to treat COVID-19 as an endemic disease. Since the pandemic, many interactions have been done online, leading to the increasing social media usage to express opinions about COVID-19. The objective of the study is to explore the capability of the Naïve Bayes algorithm in the sentiment classification of the public's acceptance on the new normal in the COVID-19 pandemic. Naïve Bayes has been chosen for its good performance in solving various other classification problems. In this study, Twitter data were used for the analysis and were collected between March and June 2022. The evaluation results have shown that Naïve Bayes could generate excellent and acceptable performance in the classification with an accuracy of 83%. According to the findings of this research, many people have accepted the new normal in their daily lives. The future works would include scrapping more data based on geolocation, improving the feature extraction technique, balancing the dataset and comparing Naïve Bayes performance with other well-known classifiers. The subsequent study could also focus on detecting the emotions of the public and processing non-English tweets.**

Keywords—Sentiment analysis; COVID-19; new normal; acceptance; naïve bayes

I. Introduction

The term "sentiment" refers to a topic that includes subjective and objective aspects and factual and non-factual factors. It transcends the difference between a positive or negative subject [1]. Sentiment analysis is an analytical technique to analyze a text that identifies the level of public sentiment or opinion on a product or service and a person, such as politicians or celebrities [2]. The new normal is the new order, habits, and behavior based on adaptation to encourage clean and healthy living [3]. The Corona Virus Disease 2019 (COVID-19) pandemic has changed people's livelihood around the globe.

Consequently, COVID-19 causes so many difficulties to deal with in people's lives, that the governments need to implement new protocols to reduce the spread of the COVID-19 infection among communities. The guidelines have become the new normal in the community's daily lives when people have suddenly been forced to adapt to all the protocols. Therefore, to mitigate the damaging effect of the COVID-19 pandemic, everyone is required to follow the Standard Operational Procedures set by the authorities in most countries. The new normal requires everyone to practice social distancing, use face masks, regularly wash hands with water and soap or sanitizer, stay at home unless necessary to go out, work from home or online learning for schools and universities [4]. Even after the infections have become less severe, people still have to take the precautions seriously.

It is necessary to break the virus chain and stop its transmission among the communities. Initially, the community was still ignorant of the virus's seriousness and was indirectly forced to adjust quickly and adapt to the new normal rules in daily life. Some people oppose the new normal life and still want to continue their old lifestyle without following health protocols and restrictions [5]. This kind of mentality may also influence others in embracing a new normal in their lives. Violations of health protocols will lead to an increase in COVID-19 cases. Implementing a new defence mechanism against a pandemic is quite challenging since it requires public engagement and acceptance of the policy required by the government [6]. In addition, due to the pandemic, any interaction was severely limited, resulting in increased digital use to obtain information about COVID-19. Therefore, social media sites such as Twitter have become essential platforms for expressing opinions, needs, and preferences. Nowadays, the community often responds to the current issues worldwide through Twitter by using tweets, retweeting others' posts, leaving a comment, or using a hashtag to spread something. A community has used Twitter to express their opinions over the increase of COVID-19 cases. The Twitter post can be a valuable source for understanding the community's acceptance towards new normal guidelines in making these new practices part of everyday habits.

As in Malaysia, after nearly two years of the pandemic, the country has entered the "Transition to Endemic" phase of COVID-10 starting from April 1, 2022, amid thousands of infections [7]. Endemic could be referred to as the constant presence, and usual prevalence of disease or infectious agent in a population within a geographic area. The transition to endemic can be considered an exit strategy.

Align with the announcement made by the Malaysia Government, this study proposes a sentiment analysis on the acceptance of the new normal in society. The tweet regarding the transition phase will be used. The Naïve Bayes algorithm has been chosen as the machine learning method for sentiment classification. The Naïve Bayes algorithm would help to classify the level of sentiments of society's responses into two categories which are negative and positive. This study aims to explore the capability of the Naïve Bayes algorithm in the sentiment analysis on the acceptance of the new normal in the COVID-19 pandemic. The Naive Bayes classifier has the advantage of requiring less training data to determine the estimated parameters needed in the classification process. Furthermore, the Naïve Bayes classifier is an algorithm frequently used for data mining because it is simple, fast to process, and easy to use with a simple model and a high-efficiency level [8].

This paper is structured as follows: Section I contains the Introduction; Section II discusses the Literature Review and Section III explains the Methodology. Section IV presents the Results and Discussion, while Section V presents the paper's Conclusion.

II. Literature Review

A. Similar Works

Several similar works are related to accepting the new normal in the COVID-19 pandemic. Table I describes the works, presenting the algorithms to solve the classification problems.

The first similar work used the Random Forest and Naïve Bayes algorithm to measure the people's sentiment toward government appeal in facing the COVID-19 pandemic [9]. Another work has implemented the Support Vector Machine Algorithm to analyze Twitter data and identify the Canadians' feelings regarding social distancing in relation to COVID-19 [10]. Research by [5] has analyzed the public's perception of social media towards the new normal during the COVID-19 pandemic in Indonesia. The study found that most Instagram users who follow religious accounts are against the new normal. The study [11] has implemented a Recursive Neural Network in analyzing the Twitter data to evaluate people's attitudes towards public health policies and events in the era of COVID-19. The tweet data analysis showed that many people's sentiments toward the stay-at-home approach were shifted because of the policy's negative consequences. Further, [12] has adopted the Latent Dirichlet Allocation (LDA) algorithm to perform sentiment, emotion, and content analysis of tweets regarding social distancing on Twitter. This research has indicated that most Twitter users supported the social distancing strategy.

In most works, the machine learning algorithms have solved the sentiment classification problems with reasonable accuracy. In this study, Naïve Bayes has been chosen due to its good performance in solving various other classification problems [13-15]. Although Naive Bayes has some drawbacks in the probability technique, it is worth exploring the algorithm's performance in solving another classification problem [16].

TABLE I. SIMILAR WORKS

	Title	**Algorithm**	**Objective**	**Result**	**Ref**
1.	Community Understanding of the Importance of Social Distancing Using Sentiment Analysis in Twitter	Random Forest Algorithm and Naïve Bayes algorithm	To measure people's sentiment toward government appeal in facing the COVID-19 pandemic.	Random Forest Algorithm had the best accuracy of 95.98%	[9]
2.	Sentiment Analysis on COVID-19-Related Social Distancing in Canada Using Twitter Data	Support Vector Machine algorithm	To analyse Twitter data and identify Canadians' feelings regarding social distancing.	SVM algorithm generated 87% of accuracy	[10]
3.	Public's Perception on social media towards New Normal during Covid-19 Pandemic in Indonesia: Content Analysis on Religious Social Media Accounts	Neuro-Linguistic Programming (NLP) method.	To discover about the public's perceptions of the government policies	The technique succeeds in solving the problem	[5]
4.	Analyzing Twitter Data to Evaluate People's Attitudes towards Public Health Policies and Events in the Era of COVID-19	Recursive Neural Network (RNN)	To track people's opinion regarding the public health policies and events during a COVID-19 pandemic.	The performance RNN is good.	[11]
5.	Understanding public perception of coronavirus disease 2019 (COVID-19) social distancing on Twitter	Latent Dirichlet Allocation (LDA)	To perform sentiment, emotion, and content analysis of tweets regarding social distancing on Twitter during the COVID-19 pandemic.	The algorithm abled to generate good result	[12]

B. Naïve Bayes Algorithm

The Naive Bayes classifier is a simple probabilistic classifier that calculates a set of probabilities by adding up the frequencies and value combinations from a given dataset. The algorithm uses the Bayes theorem and assumes that all variables are independently provided by the value of the class variable. The Naïve Bayes classifier can be trained very effectively in supervised learning and can also be used in complicated real-life situations. The Naïve Bayes algorithm is simple to understand, requires training data to estimate the parameters, is unresponsive to unrelated features, and performs well when dealing with actual data and unique data source [17]. Below are the equations that calculate the probability categories in Naïve Bayes theorem.

$$P(c \mid x) = \frac{P(x \mid c)\, P(c)}{P(x)} \qquad (1)$$

Equation (1) shows that variable c is class and variable x represents the attribute applied. P (c | x) is the posterior probability of class given attribute, P (x | c) is the likelihood, which is the probability of attribute given class, P (c) is a class prior probability. Lastly, P (x) is the predictor prior probabilities of the attribute [18].

III. METHODOLOGY

A. Data Collection

The data collection were conducted from March to June 2022. The data were scrapped by using the Twitter API. A total of 7659 observations (rows) and three variables (columns) were obtained. This data collection process used English tweets comprising sentences or popular hashtags related to the new normal. The search keys were; “face mask”, “hand hygiene”, “Sejahtera scan”, “new normal COVID-19”, “stay at home”, “work from home” and “social distancing”. Table II shows the sample of a raw dataset from the scrapping process. The dataset contains three columns which represent Time, User and Tweet. However, only the Tweet column was used in this study.

B. Data Pre-processing

Data cleaning is the terms that refer to the process of identifying and correcting, removing, duplicate or invalid records from a database. Data inconsistency can occur in a variety of ways. For example, it might occur due to data corruption during transmission or storage or user entry errors [19]. Therefore, it is essential to clean up data so it can be used in models and produce better results.

TABLE II. SAMPLE OF RAW DATASET

Time	User	Tweet
2022-04-10 23:51:57+00:00	EnviroSmartGOP	#SocialDistancing , #lockdowns and changes to age-old ,PROVEN , #Quarantine methods of isolating sick , infectiousâ€¦ https://t.co/f7PShlaAOk
2022-04-10 23:22:20+00:00	MissyCooper13	RT @JohnSitarek: Mass PCR testing somewhere in #Eastworld. If you didn't have covid before standing in line for hours, you probably contracâ€¦
2022-04-13 17:20:01+00:00	NoxySA3	@thecyrusjanssen you are reminded to get vaccinated, wear face mask and to use sanitizer to wash your hands #VaxxedForAfrica
2022-07-13 23:15:44+00:00	ThatTeddyH	RT @R_Chirgwin: Wear your masks. Avoid crowds. Work from home. Keep your children home. Drag these recalcitrant mendacious fools into line.â€¦

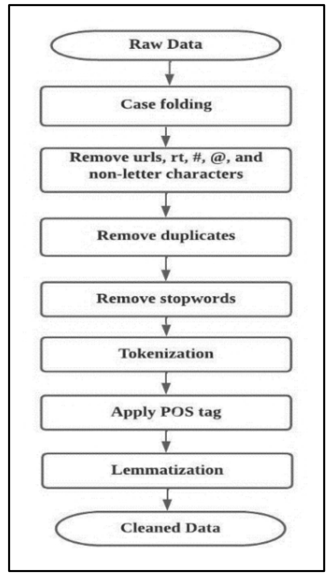

Fig. 1. Steps in Pre-processing.

Fig. 1 shows the steps of the data pre-processing for this study. Firstly, the tweets are converted into lowercase, while symbols and numbers are ignored. The website links such as “https” or “www”, retweets (rt), the hashtag symbol (#), user handles (@), and non-letter characters are also eliminated from the tweets. These are replaced with a blank string. After case folding, all the duplicate rows are removed to prevent redundancy in the dataset. Then, stopword removal is applied to the clean dataset, which removes stopwords listed in the NLTK package. To remove the stopwords, the lambda function is used. After stopwords removal, the tweet is tokenized. In tokenization, all text sentences are broken down into smaller parts called tokens. The Part-Of-Speech (POS) is applied after the data has been tokenized. The POS tagging determines the word class based on the word's placement in the sentences, indicating whether the word is a noun, adjective, verb, etc. and also enables future use of lemmatization.

The pos tags of a word are important to obtain the word’s lemma properly. The final step in the process involves lemmatization steps being applied to the dataset. This is done because lemmatization has the potential to give meaningful root words. Lemmatization is preferred over stemming because it produces better results by performing an analysis based on the word's part and producing true dictionary words. Atfer the preprcessing, the datasets were reduced to 2807 data. This is mainly because the pre-processing steps have eliminated all the noisy and unnecessary data.

C. Labelling

After the pre-processing, the processed tweets data must go through the labelling process. The labelling process is intended to label the data according to the sentiment classes, which is negative and positive [3]. Text Blob, a python library, has been used in this process. The positive tweets is represented by the number (+1), negative is represented by the number (-1) and neutral is represented by (0). In this study, only positive and negative classes are used. Table III shows an example of tweets labelled with positive and negative sentiments. After the labelling, there are 2095 positive tweets, while the negative tweets obtained are 712.

TABLE III. EXAMPLE OF TWEETS LABELLED WITH POSITIVE AND NEGATIVE SENTIMENT

Tweet	Label
Keep hands clean, wear a mask for no more than a couple of hours and dont touch your face is the best advice.	1
I am sick of having to wear masks and have no face anymore. I don't want to wear a mask.	-1

D. Feature Extraction

Bag-of-Words is a method that has been used for feature extraction. Bag-of-Words is the most used technique for natural language processing. In this process, the bag-of-word extracts the words or the features from a tweet, and then the frequency of each term is calculated. It is called a “bag” of words because any information about the order or structure of words in the document is discarded. The model is only concerned with whether known words occur in the document, not where in the document [20].

As in this study, the bag of words model calculates the number of tokens collected in each document. Fig. 2 shows the output for the bag of words process. It displays the frequency table that counts how many times the term appeared. It contains three columns: the index representing the words, the count representing the occurrence of the terms, and the label representing each word's positive and negative labels.

E. System Architecture

The proposed system architecture is shown in Fig. 3. The first step is collecting the tweets from Twitter by using the Twitter API. The collected tweets are stored in the database and will go through the pre-processing steps. Then, the data is labelled with the positive or negative tag. Next, the data will be split into training and testing data. The training data will be used for feature extraction. The data is then passed to the Naive Bayes classifier model to categorize the data into positive or negative classes. The output result will show the accuracy of the proposed algorithm. Finally, the sentiment analysis result will be displayed to the user through the graphical user interface [21].

	index	count	label
0	there	0	-1
1	nothing	6	-1
2	special	0	-1
3	born	0	-1
4	thing	16	-1
...	...	...	...
11639	gmfu	0	1
11640	realtor	1	1
11641	propey	1	1
11642	willing	1	1
11643	matt	1	1

Fig. 2. Bag of Words Model.

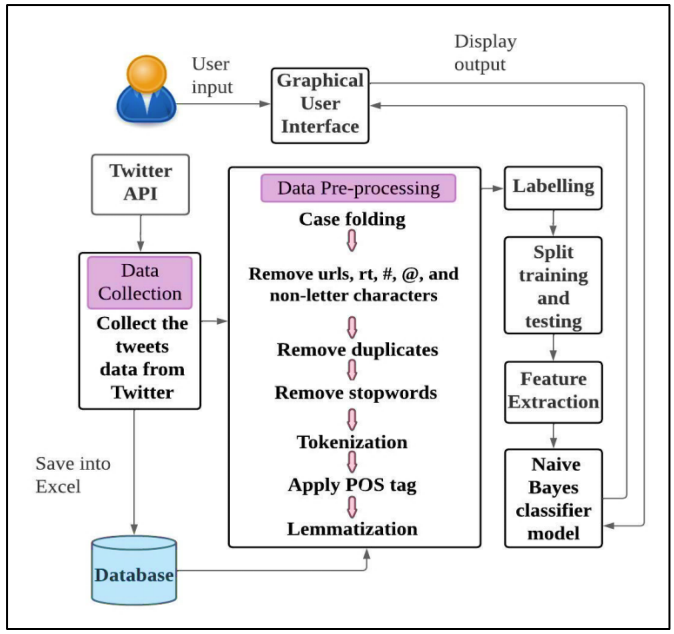

Fig. 3. Proposed System Architecture.

F. Performance Evaluation

Holdout method and Confusion Matrix have been used to evaluate the performance of the Naïve Bayes classifier. The holdout method is the simplest method to evaluate the performance of classifier where the data will be randomly split into two sets, which are training and testing set. The training data set is used to train the Naïve Bayes classifier and the testing dataset is used to test the performance of the classifier. Three sets were used in this study which are 90:10, 80:20 and 70:30. The first number for example for 90:10, indicates the percent of data used for training and the latter is for testing.

In addition, a confusion matrix is a matrix that comprises information on the actual and predicted classification achieved by classifier. It is often used to measure the performance of a classification algorithm. It includes the measurements of accuracy, precision, recall, F1-scores and ROC curve. The confusion matrix gives us a better picture of the algorithm's performance [22].

Table IV illustrates the confusion matrix for two classes which is for actual and predicted. The terms TP and TN indicate the True Positive and True Negative, which are referred to the accurately classified data. Meanwhile, FP and FN represent False Positive and False Negative, indicating incorrectly classified data [23].

TABLE IV. CONFUSION MATRIX

	Actual Positive	Actual Negative
Predicted Positive	TP	FP
Predicted Negative	FN	TN

The classifier accuracy can be calculated by applying the formula in (1). The accuracy presents the ratio of correct prediction over the total data. For the precision, it is indicated as the measure of the correctly identified positive cases from all the predicted positive label. Next, for the recall, it measures the correctly classified positive from the total of the actual positive. As for the F1-score, it is the combination of precision and recall of a classifier into a single metric by using the harmonic mean [24]. The formulas to calculate the accuracy, precision, recall and F1-score are presented in the (1) to (5) respectively.

The accuracy obtained from (2) below:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{2}$$

The Precision obtained from (3) below:

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

The Recall obtained from (4) below:

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

The F1-Score obtained from (5) below:

$$F1\ Score = 2 \times \frac{precision \times recall}{precision + recall} \tag{5}$$

Another classifier performance evaluation is the Receiver Operating Characteristic (ROC) curve. The ROC curve is a graph that summarizes the model's performance by integrating the confusion matrices at all threshold values [25]. Therefore, the ROC curve could provide an overview of the model's performance at different threshold values [26]. It is a graphical representation of the paired classifier with the bend indicating a trade-off between positive and false positive.

IV. Result and Discussion

There are two main analyses that have been conducted in this study. The first analysis conducted was the exploratory data analysis on the collected tweets data. Then, the second analysis was on the performance of the Naïve Bayes Classifier. In addition, the prototype to be used with the classifier model was proposed at the end of this section.

A. Exploratory Data Analysis

The first analysis is by analyzing the most common word obtained from the tweet. Fig. 4 shows the bar chart which is plotted to obtain the common words for the topics of acceptance of new normal in the COVID-19 pandemic. This chart provides an overview of which words frequently appear in the dataset. It reveals that the most common terms are new, home, normal, work, social, distancing, mask, wear, and stay. These top 10 common words have shown that people are aware of the pandemic's new normal lifestyle.

Then the analysis continues by analyzing the dataset according to its label which are positive and negative sentiment. The analysis conducted were word cloud and unigram analysis. A word cloud is one of the most common techniques for displaying and analyzing qualitative data. It is a graphic consisting of keywords found in the body of text, with the size of each keyword indicating the frequency with which it appears in the body of text [27].

Fig. 5 shows the word cloud for positive dataset, The most prominent words are "social", "distancing", "new", "normal", "hand", "hygiene", "mask", "job", and "home". These words indicate the most discussed topic during the pandemic. It is used to represent positivity and actions during the pandemic. On the other hand, Fig. 6 the word cloud for negative dataset. We can observe some of the negative words such as "ill", "don't", "sick", "hate", "shit", and "pandemic" from the word cloud.

The count of word in positive and negative dataset using unigram analysis were also identified. The unigram is the single word representation in the dataset. Fig. 7 shows the positive dataset's top 10 words: new, normal, home, social, work, mask, get, distancing, wear, and hand. The most used phrase is "new". While Fig. 8 shows the top 10 words in the negative dataset: home, work, mask, get, normal, new, people and hand. The words in both unigrams mostly are the same, but the count for all words is different. For example, the term "new" in the positive Data Frame is more than 400, while the word "new" on the negative side is less than 100.

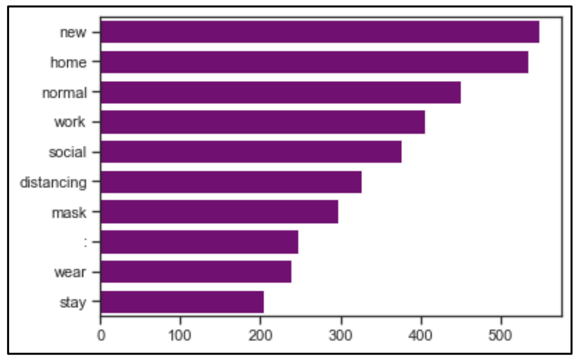

Fig. 4. Top 10 Common Words.

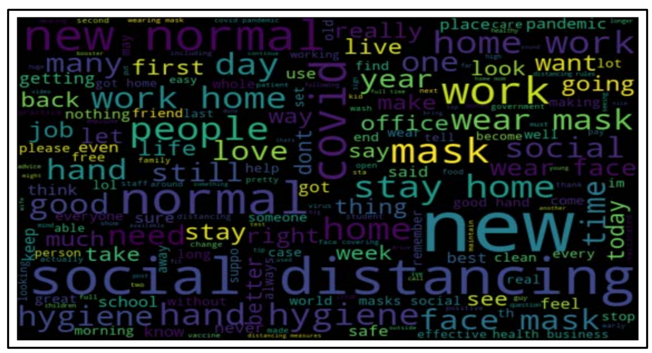

Fig. 5. Word cloud for Positive Datasets.

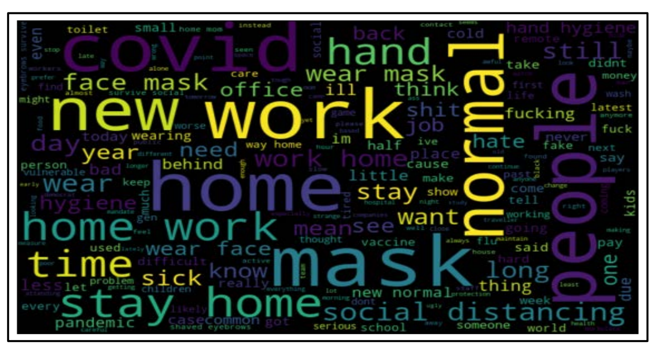

Fig. 6. Word cloud for Negative Dataset.

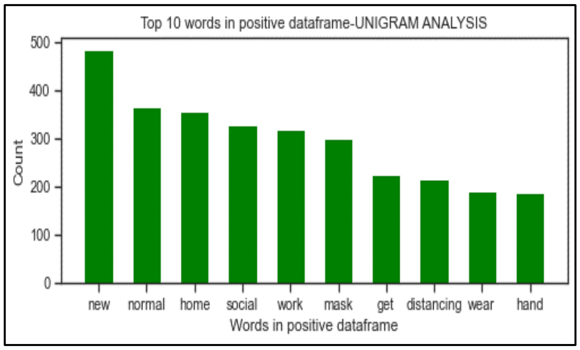

Fig. 7. Unigram Analysis for Words in Positive Dataset.

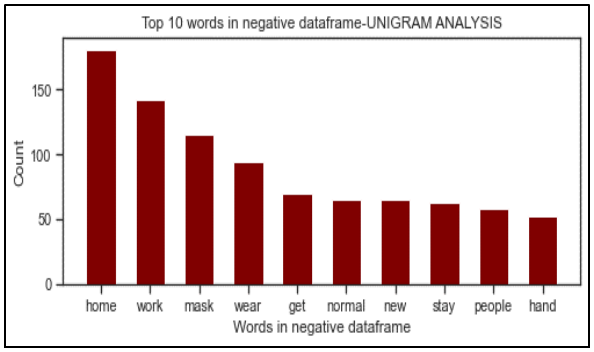

Fig. 8. Unigram Analysis for Words in Negative Dataset.

B. Naïve Bayes Classifier Performance Evaluation

This section discussed the performance of the Naïve bayes classifier. The first performance was evaluated by looking at the accuracy of the classifier to classify the sentiment of the tweet data. It is done by comparing the actual label in testing data with the predicted label provided by the classifier. In this study, the accuracy was calculated by using the sklearn library in python. Table V presents the accuracy results. Based on the testing, the best accuracy is 83%, and the minimum is 79%.

To better understand the classifier performance, a confusion matrix was used. The analysis is focused on the 90:10 dataset, which obtained the best accuracy result. In this dataset, 281 data were tested. The confusion matrix obtained is shown in Fig. 9. The figure shows that there are 180 positive data and 54 negative data that the model has correctly predicted. However, the Naïve Bayes model cannot predict the remaining 47 data.

The confusion matrix can calculate the accuracy, precision, F1-score and recall of the Naive Bayes model. Fig. 10 shows the detailed result of the classifier performance. The weighted average for precision, recall and F1- Score is 0.85, 0.83 and 0.84, respectively. Based on these values, even though the dataset contains an imbalance number of positive and negative data, the Naïve Bayes classifier can do the classification with 84% as indicated by the F1-score. In addition, all the parameters show a consistent value, such as the accuracy of the model.

Fig. 11 shows the ROC curve for the Naïve Bayes model. The true positive rate (TPR) is plotted against the false positive rate (FPR) to create a ROC curve (FPR). The actual positive rate (TP/ (TP + FN)) is the proportion of positive observations that were correctly expected to be positive out of all positive observations. The closer the ROC curve approaches the upper left corner of the plot, the more effectively the model classifies data. To determine how much of the plot falls under the curve, the AUC (area under the curve) is used. The AUC value for Naïve Bayes model is 0.82. The greater the AUC, the better the model's ability to distinguish between the positive and negative classes of data [28].

TABLE V. ACCURACY OF THE CLASSIFIER FOR EACH DATASET

Split dataset	Train data	Test data	Accuracy
90:10	2526	281	83%
80:20	2245	562	81%
70:30	1964	843	79%

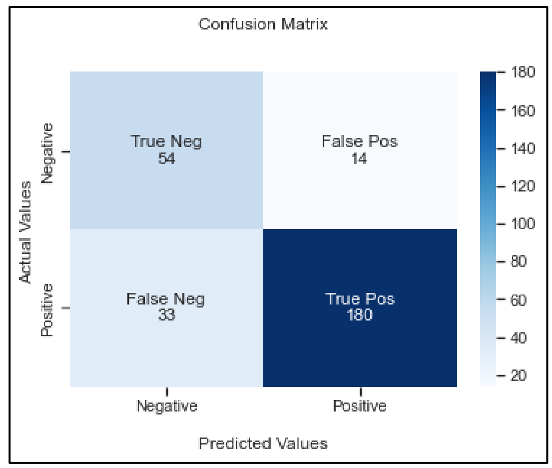

Fig. 9. Confusion Matrix for 90:10 Split Dataset.

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Classification report :

              precision    recall  f1-score   support

          -1       0.62      0.79      0.70        68
           1       0.93      0.85      0.88       213

    accuracy                           0.83       281
   macro avg       0.77      0.82      0.79       281
weighted avg       0.85      0.83      0.84       281
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Fig. 10. Classification Report.

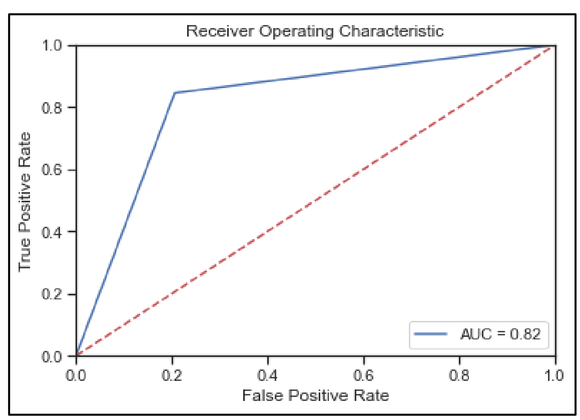

Fig. 11. ROC Curve.

This study also compares the accuracies of the Naïve Bayes algorithm implemented in other similar works. Table VI shows the accuracies of Naïve Bayes in each of the studies. Based on Table VI, the Naïve Bayes algorithm has generated good accuracies of more than 80% in all similar works. A Naïve Bayes algorithm could produce good and acceptable performance in sentiment classification problems. It is proven that Naïve Bayes is a reliable classifier due to its capabilities in solving various classification problems.

TABLE VI. COMPARISON OF NAÏVE BAYES ACCURACY BETWEEN SIMILAR WORKS

Authors	Accuracy
[3]	80.37%
[9]	80.65%
[29]	84.1%
Proposed Naïve Bayes Classifier	83%

C. The Proposed Prototype

A prototype has been proposed for the implementation of the classifier. Fig. 12 displays the main user interface for the sentiment analyzer system. The user prototype was developed using the Python library's Tkinter framework. In the system, the user needs to input the sentiments first and then click on the "Check Sentiment Result" button to obtain the sentiment results. The result will then show the category of the tweets, whether it is Positive or Negative. The user needs to click on the “Clear” button to analyze the following statements. In this initial development, the system could only process one tweet at a time. The next improvement would enable the system to process several tweets simultaneously.

Fig. 13 shows the model’s accuracy interface. If the user wants to see the model's accuracy in predicting the sentiment, the user must click the "Check Accuracy" button. It will navigate the user to a new window that shows the accuracy. The "Exit" button is used to close the system.

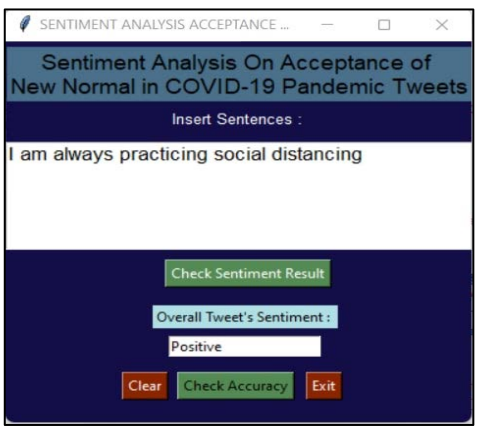

Fig. 12. Main Interface.

Fig. 13. Model's Accuracy Interface.

D. Research Limitation

Several limitations of this study have been identified during the project's development. The first one is the quantity of data that has been scrapped is quite small. It is due to the time constraints of the project. Also, the standard API only allowed to retrieve tweets up to seven days and has a limited number to retrieve the data. This is because of the restriction on the Twitter developer account. In addition, the distribution of negative and positive tweets is also unbalanced. This might affect the performance of the classifier [30].

The next limitation is emotion analysis, which is not considered in this project. This project cannot indicate the public’s emotion toward the new normal issues in the COVID-19 pandemic. The emotions are such as the people feel angry, surprised, happy or sad about accepting the new normal in their daily life. Lastly, the scraped tweets are limited to English tweets and are not filtered by specific locations. The insight could not be generalizable to non-English speaking populations if only English tweets are used as the dataset. In addition, since most tweets do not have geolocation, it could be lacking in making conclusions based on certain countries or regions [31].

V. CONCLUSION

This study has successfully explored the capability of the Naive Bayes algorithm in solving the sentiment classification on the acceptance of new normal in the COVID-19 pandemic. A total of 2807 tweets have been processed, which consisted of 2095 positive and 712 negative tweets. Based on the evaluation results, Naive Bayes has generated good and acceptable performance with 83% accuracy and 84% of F1-score. In addition, the developed Naïve Bayes classifier can distinguish between positive and negative tweets as indicated by AUC value of 0.82.

The significance of this study is in demonstrating the capability of the Naïve Bayes classifier in sentiment analysis. The proposed conceptual framework shown in Fig. 3 can be used as a guideline in conducting similar works. As for the study on the acceptance of the new normal in the COVID-19 pandemic, exploratory data analysis on the tweets showed more positive sentiments than negative ones. This indicates that most people could accept the new normal in their daily life during the COVID-19 pandemic.The government could use the results of this study as a resource for consideration in developing policies and campaigns and making approaches to the people to implement the new normal. This study could help the ministry of health deliver the necessary messages to the public while also addressing public concerns and encouraging positive behaviour in response to the COVID-19 pandemic.

Future works would be to include the public's emotions and to process non-English tweets. The next scrapped Twitter data would also be based on geolocation, so that data could be analyzed based on particular countries or regions.

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