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Analysis of Citizen's Sentiment Towards Philippine Administration's Intervention Against COVID-19

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ABSTRACT

The study focused on analyzing the sentiment of the public towards the initiatives of the government in mitigating the effect of COVID-19 pandemic in the country. A sentiment classifier model was developed by integrating Support Vector Machine to the layers of Bidirectional Recurrent Neural Network-Long Short Term Memory (BRNN-LSTM + SVM). The result of the study shows that the sentiment classifiers achieved better accuracy when corpora-based sentiment lexicon was used to determine the sentiment polarity of the datasets. This is because the sentiment lexicon was able to capture the context of each word used in the datasets. The proposed hybrid sentiment classifier achieved a 93% accuracy for the Twitter dataset and 95% accuracy for the Facebook dataset. The ability of the model in classifying text data was further improved by integrating stemming process. The results indicate that the citizens harbor negative sentiments towards the initiatives of the government in mitigating the effects of the COVID-19 pandemic.

Keywords: COVID-19, Sentiment analysis, Bidirectional recurrent neural network, Long short-term memory, Support vector machine, Social computing

INTRODUCTION

SARS-CoV-2 virus, popularly known as COVID-19, is a communicable disease that affected 114 countries since it started in the year 2019. On March 11, 2020, the World Health Organization officially categorized the disease as a pandemic due to the increasing number of cases around the world. To date, there have been 252,902,685 cumulative cases from all over the world since the pandemic started (WHO 2021). To prevent the rapid spread of the disease, WHO issued guidelines that the public should follow. Following the guidelines set by WHO, the Philippine government imposed several restrictions and initiatives to mitigate the effect of the pandemic. Some of the initiatives implemented by the government include travel restrictions, community quarantine, and suspension of face-to-face classes and work arrangement to name a few (Inter-agency Task Force 2020). These initiatives have triggered untimely closure of some business establishments and unemployment due to the economic downturn during the pandemic. The initiatives imposed by the government, the situation of the country during the

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pandemic, and how the situation is being handled have resulted in different reactions from the citizens. These reactions are mostly expressed using several social media platforms.

During the pandemic, social media platforms served as a medium for the government and WHO to provide relevant information to the citizens about the COVID-19 situation in the country. Among these social media platforms are Facebook and Twitter. As of March 2021, Facebook reported that there are about 1.88 billion daily active users (Facebook 2021) and 199 million Twitter users (Twitter 2021). Due to a large number of users on these platforms, they were used as a means to report daily updates about COVID-19 situation in the country. These platforms allow the citizens to express their sentiments about how the government handles the pandemic (Imran et al. 2013). These sentiments can provide information about the thoughts of the citizens towards these initiatives.

The nature of posts and tweets can be qualified as unstructured and noisy textual data. This is because social media users tend to use shortened and misspelled words when writing posts and tweets due to the limited characters allowed (Bhargava et al. 2019, Virmani et al. 2017, Habib and van Keulen 2014). They also don't use explicit sentiment words to express their opinion which makes it hard to classify whether the text expresses positive or negative sentiment (Son et al. 2019, Wei et al. 2019). Another challenge that needs to be addressed in the field of sentiment analysis is the use of colloquial and curse words which are not recognized in the Standard English dictionary. In addition, Filipino social media users tend to use mixed language or dialect in writing comments, posts, and tweets. This poses a challenge in the field of sentiment analysis since most of the sentiment classifier models are designed to classify text data written in one language (Bhargava et al. 2019). In addition, although there are sentiment lexicons available, very few are designed for text data written in the Filipino language that includes colloquial and curse words (Samuel et al. 2020).

In this study, a hybrid Bidirectional Recurrent Neural Network - Long Short-Term Memory - Support Vector Machine (BRNN-LSTM+SVM) sentiment classifier model was developed to determine the sentiment of the citizens towards the initiatives of the Philippine government in mitigating the effects of COVID-19 pandemic in the country. The performance of the model was measured and compared to the performances of the native Bidirectional Recurrent Neural Network and Support Vector Machine in classifying posts and tweets about the pandemic.

The main contribution of the paper is the development of a hybrid sentiment classifier model to determine the sentiment of the public towards the different initiatives imposed by the government during the pandemic. In addition, a method in generating a corpora-based COVID-19 sentiment lexicon was designed and implemented. Lastly, a COVID-19 sentiment dataset was created from both Twitter and Facebook datasets.

The remainder of this paper is outlined as follows, Section 2 discusses the methodology employed in the study, Section 3 provides the discussion of the results after performing a series of experiments, and Section 4 provides the conclusion and future direction of the study.

METHODOLOGY

Data Collection and Annotation

The dataset collected came from Facebook and Twitter from March 2020 to August 2020. The dataset collected was based on the keywords related to the initiatives of the Philippine government. The initiatives used as a basis for keywords searched, include travel restrictions, community quarantine, social amelioration program, 'Balik-probinsya' program, suspension of face to face classes and work arrangement, among others. The tweets and comments were extracted using Facebook and Twitter API and www.exportcomments.com. After performing the extraction process, there were 16,000 tweets and comments collected. 25% of the collected tweets and comments were manually annotated. The manually annotated dataset was used to establish the ground truth for the study. The human annotators also corrected words that are misspelled and inappropriately abbreviated which helps the automatic translator in translating the dataset. To determine the raters' consistency test, the result of the labeling process was tested using Cohen Kappa's inter-rater reliability (McHugh 2012). The computed kappa value was 0.78 which is interpreted as a substantial agreement which means that the agreement between the annotators is considered acceptable.

Preprocessing Stage

Preprocessing was performed to clean the Twitter and Facebook datasets. It includes the conversion of characters to lowercase, removal of URL, removal of punctuation marks, removal of texts containing pure numbers, removal of irrelevant comments such as those that provide financial advising and information regarding flight cancellations, and removal of stopwords, and stemming. The task also includes the translation of the dataset to the English language. A python program, which implements Google Translate API, was written to perform the translation. The translated dataset was used to build a word list which was tagged with their appropriate part of speech labels using NLTK POS tagger.

Generation of Corpora-based Sentiment Lexicon

Sentiment lexicon was built using the words included in the word list and was tagged as a verb, adjective, and adverb (Zhang et al. 2018, Deng et al. 2019). It also includes those words tagged as curse words (Samuel et al. 2020) and hashtags since they convey sentiments relevant to the study. Each word from the word list is read and checked in the manually labeled dataset to determine which sentence does the word mostly appears. These words are labeled as positive, negative, or neutral. Words that are labeled as neutral are excluded from the sentiment lexicon.

Sentiment Polarity Identification

The sentence sentiment polarity was identified by determining the sentiment orientation of each word in a sentence based on a sentiment lexicon. The sentiment score is computed based on the difference of the number of word sentiment polarity. These sentences are labeled as positive, negative, or neutral.

Building the Model

For this study, the hybrid approach of BRNN-LSTM-SVM was built by integrating the SVM as one of the layers of the BRNN-LSTM model. SVM is the last layer of the BRNN-LSTM model. The preprocessed dataset was divided into training, validation, and testing set. 80% of the dataset was randomly selected for training and the remaining 20% was left for validation and testing. Global Vector (GloVe) was used to generate word embeddings for the dataset. The generated word embeddings were used as input to the input layer of the model. To avoid overfitting, a 10-fold cross-validation was implemented.

Performance Evaluation

In this study, the performance of the proposed hybrid BRNN-LSTM + SVM model is compared to the performance of the traditional machine learning models, BRNN-LSTM and SVM. The performance of these models was compared in terms of the sentiment lexicon used and in classifying Facebook and Twitter datasets. The metrics used to measure the performance of the proposed hybrid sentiment classifier model includes precision, recall, f1-score, and accuracy.

RESULTS AND DISCUSSION

Sentiment Polarity of Facebook and Twitter COVID-19 Datasets

The COVID-19 Corpora-based sentiment lexicon and NRC sentiment lexicon were used as the basis for identifying the sentiment polarity of each sentence in the unlabeled Twitter and Facebook datasets. Table 1 shows the comparison of the sentiment polarity of the datasets using the two lexicons.

Using Corpora-based sentiment lexicon, 53% of the sentences from both Twitter and Facebook datasets has negative sentiment. This surpassed those sentences/documents with Neutral and Positive sentiments (see Table 1). On the other hand, the NRC sentiment lexicon has resulted to a different sentiment orientation for both datasets. As observed in table 1, 48.36% of the Facebook dataset was tagged with Positive sentiment which covers the majority of the dataset. For the Twitter dataset, Tweets tagged with Positive and Negative sentiments are almost the same in number which covers around 35% to 37% of the entire dataset.

Both datasets labeled using these sentiment lexicons were used to train, validate, and test the machine learning models for performing sentiment classification tasks.

Sentiment Classifier Model Performance Based on Sentiment Lexicons

The performance of the sentiment classifier models were measured by using the datasets that are automatically labeled using the corpora-based sentiment

Table 1. Comparison of sentiment polarity using the two lexicons.

Dataset	Polarity	Corpora-based Sentiment Lexicon	%	NRC Sentiment Lexicon	%
Facebook	Negative	4218	53.25	1950	24.62
	Neutral	3371	42.56	2140	27.02
	Positive	332	4.19	3831	48.36
	Total	**7921**	**100.00**	**7921**	**100.00**
Twitter	Negative	4279	53.49	3003	37.54
	Neutral	3395	42.44	2172	27.15
	Positive	326	4.07	2825	35.31
	Total	**8000**	**100.00**	**8000**	**100.00**

Table 2. Comparison of sentiment classifier models based on two lexicons using the Facebook dataset.

Lexicons	Sentiment Classifiers	Precision		Recall		F1-score		Accuracy
		Neg.	Pos.	Neg.	Pos.	Neg.	Pos.	
Corpora-based Sentiment Lexicon	SVM	91.00%	93.00%	94.00%	85.00%	92.00%	89.00%	90.00%
	BRNN	98.00%	72.00%	98.00%	68.00%	98.00%	70.00%	96.00%
	BRNN-LSTM+SVM	96.00%	79.00%	99.00%	45.00%	97.00%	57.00%	95.00%
NRC Sentiment Lexicon	SVM	73.00%	92.00%	87.00%	84.00%	79.00%	88.00%	81.00%
	BRNN	89.00%	94.00%	88.00%	94.00%	88.00%	94.00%	92.00%
	BRNN-LSTM+SVM	88.00%	92.00%	84.00%	94.00%	86.00%	93.00%	91.00%

Table 3. Comparison of sentiment classifier models based on two lexicons using the Twitter dataset.

Lexicons	Sentiment Classifiers	Precision		Recall		F1-score		Accuracy
		Neg.	Pos.	Neg.	Pos.	Neg.	Pos.	
Corpora-based Sentiment Lexicon	SVM	92.00%	90.00%	91.00%	86.00%	92.00%	88.00%	89.00%
	BRNN	96.00%	74.00%	98.00%	52.00%	97.00%	61.00%	95.00%
	BRNN-LSTM+SVM	93.00%	75.00%	100.00%	16.00%	96.00%	27.00%	93.00%
NRC Sentiment Lexicon	SVM	89.00%	86.00%	78.00%	85.00%	83.00%	85.00%	81.00%
	BRNN	85.00%	91.00%	93.00%	82.00%	89.00%	86.00%	88.00%
	BRNN-LSTM+SVM	87.00%	85.00%	87.00%	85.00%	87.00%	85.00%	86.00%

lexicon and NRC sentiment lexicon (Mohammad and Kiritchenko 2020). The automatically labeled datasets were used to train, validate, and test the performance of sentiment classifiers. Tables 2 and 3 show the performance of the models based on the automatically labeled datasets using both sentiment lexicons.

Table 4. Comparison of sentiment classifier models using two different datasets.

Datasets	Sentiment Classifiers	Precision		Recall		F1-score		Accuracy
		Neg.	Pos.	Neg.	Pos.	Neg.	Pos.	
Facebook	SVM	91.00%	94.00%	95.00%	86.00%	93.00%	90.00%	91.00%
	BRNN	98.00%	72.00%	98.00%	68.00%	98.00%	70.00%	96.00%
	BRNN-LSTM+SVM	96.00%	79.00%	99.00%	45.00%	97.00%	57.00%	95.00%
Twitter	SVM	92.00%	90.00%	91.00%	86.00%	92.00%	88.00%	89.00%
	BRNN	96.00%	74.00%	98.00%	52.00%	97.00%	61.00%	95.00%
	BRNN-LSTM+SVM	93.00%	75.00%	100.00%	16.00%	96.00%	27.00%	93.00%

It can be observed that even though the same datasets were used as inputs into the sentiment classifier models, there is still a difference in terms of their performance which can be attributed to the sentiment lexicons used to identify the dataset's polarity. It can be gleaned that for both Facebook (see Table 2) and Twitter (see Table 3) datasets, the sentiment classifier models produced higher accuracy when corpora-based sentiment lexicon was used to identify the polarity of both datasets. Since corpora-based sentiment lexicon was generated based on the corpus used in the study, the sentiment of each word contained in the lexicon was based on the context in which these words were used.

The use of generated Corpora-based sentiment lexicon has proven to be effective in improving the performance of machine learning algorithms such as SVM in performing several text classification tasks including sentiment analysis and topic modeling (Lin et al. 2014, Deng et al. 2019).

Sentiment Classifier Model Performance Based on Two Datasets

The performance of sentiment classifier models was also measured and compared based on the datasets used (see Table 4).

It can be observed that SVM performs better with a Facebook dataset with 91% accuracy compared to its performance using the Twitter dataset with 89% accuracy. Likewise, BRNN, with 96% accuracy, and BRNN-LSTM + SVM, with 95% accuracy, perform better when the Facebook dataset was used compared to their performance using the Twitter dataset.

In addition, it is important to note that even though the accuracy of the models are high, there are drawbacks concerning its ability to classify datasets with positive sentiment. As shown in Table 4, each model (for both Twitter and Facebook datasets) posed high precision, recall, and F-score for identifying textual data with negative sentiment. However, the same metrics are relatively low when dealing with textual data having positive sentiment. This means that even though the sentiment classifier models achieved relatively high accuracy, it would be easier for the model to detect textual data with the negative sentiment but may suffer detecting textual data with positive sentiment. To address this concern, stemming was applied for both datasets.

Table 5. Comparison of sentiment classifier models using two different datasets after Stemming.

Datasets	Sentiment Classifiers	Precision		Recall		F1-score		Accuracy
		Neg.	Pos.	Neg.	Pos.	Neg.	Pos.	
Facebook	SVM	82.00%	86.00%	98.00%	87.00%	89.00%	87.00%	90.00%
	BRNN	97.00%	92.00%	96.00%	92.00%	96.00%	92.00%	95.00%
	BRNN-SVM	94.00%	91.00%	96.00%	87.00%	95.00%	89.00%	93.00%
Twitter	SVM	84.00%	74.00%	97.00%	86.00%	90.00%	79.00%	90.00%
	BRNN	97.00%	90.00%	98.00%	87.00%	97.00%	89.00%	95.00%
	BRNN-SVM	93.00%	94.00%	99.00%	70.00%	96.00	80.00%	93.00%

The performance of the models after applying the stemming process is shown in Table 5.

It can be observed that the accuracy achieved by the SVM, BRNN, and hybrid BRNN-LSTM + SVM sentiment classifiers declined when stemming was applied to the Facebook dataset. On the other hand, a slight increase in accuracy was observed on the stemmed Twitter dataset for SVM. In addition, the accuracy achieved for BRNN and hybrid BRNN-LSTM + SVM after applying stemming to the Twitter dataset was maintained even before the dataset underwent the stemming process. However, it is important to note that even though the accuracy of the models declined after applying stemming, the precision, recall, and F-score for determining textual data with positive sentiments increased. This means that the stemming process helped the models for detecting both positive and negative sentiments among textual data by overcoming lexical sparsity and issues on ambiguity (Elfaik and Nfaoui 2021). Hence, it indicates that the sentiment classifier model, when implemented with stemming, has a small error rate and will be more accurate in predicting classes of objects (Rianto et al. 2021).

CONCLUSION AND FUTURE WORK

The study contributes to the body of knowledge in the field of natural language processing by proposing a hybrid model for classifying non-English text data for their sentiments. By conducting series of experiments, it was found out that the use of corpora-based sentiment lexicon for determining sentence sentiment polarity helps improve the performance of the hybrid model in classifying textual data. This is because the sentiment lexicon was able to capture the context of each word used in the datasets. However, it is important to note that gaining higher classification accuracy may pertain to its ability to classify one sentiment class but may suffer identifying the other class. Hence, the stemming process was proven to be effective in improving the performance of the sentiment classifier models in classifying the text data for both sentiment classes.

As shown in the study, the results indicate that the citizens harbor negative sentiments towards the initiatives of the government in mitigating the effects of the COVID-19 pandemic. The government can use the result of the study as a basis in evaluating the initiatives implemented during the pandemic and to further refine the existing plans related to current crisis.

For future work, other existing deep learning models may be combined with the proposed model to improve its performance. Other features such as n-grams may also be considered to improve the performance of the proposed model. Furthermore, the impact of increasing and decreasing hidden layers in a deep learning model in performing sentiment analysis may also be considered for future work.

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