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Analysis of Public Sentiment Towards Goverment Efforts to Break the Chain of Covid-19 Transmission in Indonesia Using CNN and Bidirectional LSTM

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Abstract

COVID-19 is a new disease that has a negatively impacts in Indonesia, so the government is taking several measures to suppress the spread of COVID-19, such as new normal, social distancing, health protocols fines, and COVID-19 vaccination. The government's handling efforts have reaped a variety of negative to positive responses from the public on social media, so this study aims to determine the effectiveness of the government's efforts by analyzing public sentiment using the Deep Learning method with 1,875 training datasets consisting of four types government efforts and taken from various media social. The use of Deep Learning begins with testing several Deep Learning architectures to determine the best architecture for predicting data. The architectures tested include CNN and Bi-LSTM, where from these tests, Bi-LSTM outperforms CNN with the best performance achieving the accuracy of 97.34% and 97.33% for precision, recall, and F1-score. The results of public sentiment analysis show that social distancing efforts are considered the most effective by obtaining the most positive sentiments by 33.93%, while the effort to health protocol fines is considered lacking because it obtains the most negative sentiment of 35.64%, so the government must continue to enforce social distancing and optimize other efforts that are still considered ineffective.

Keywords: *COVID-19, Deep Learning, Bidirectional LSTM, CNN*

1. Introduction

At the end of 2019, the world was shocked by the emergence of a new disease outbreak with symptoms similar to Pneumonia that occurred in Wuhan, Hubei, China [1]. This disease was initially named 2019 novel coronavirus (2019-nCoV), then the World Health Organization (WHO) announced a new name on February 11, 2020, as Coronavirus Disease (COVID-19) caused by Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) Virus. The first COVID-19 was reported to have entered Indonesia on March 2, 2020 [2]. The increase in the number of cases occurred quickly, so it needed immediate treatment. There are many negative impacts caused by the spread of COVID-19 disease in Indonesia, so the government is trying to take several actions to reduce the spread of COVID-19, such as new normal, social distancing, health protocols fines, and COVID-19 vaccinations. Responses from the Indonesian people to some of the government's efforts are pretty diverse on various social media, some support it, and some do not agree [3]. Social media users can share aspirations, opinions, and criticisms to social media that contain various positive and negative meanings, so it is necessary to analyze sentiment on public opinion regarding the government's handling of the Corona Virus with positive, negative, and neutral classifications.

Sentiment analysis is carried out to understand and process textual data automatically to see the sentiment contained in an opinion [4]. The use of the Deep Learning method was chosen because it is able to analyze complexly, even on simple data. The sentiment analysis process with the Deep Learning method is carried out by processing many layers of nonlinear information to carry out the process of feature extraction, pattern recognition, and also classification [5].

Research related to the topic of COVID-19 is being intensified because of the negative impact caused by the spread of COVID-19 on areas of life such as social, economic, and education. Various methods are used in COVID-19 research, such as the research conducted by Deepak Kumar & Tajebe Tsega Mengistie on user views on the pandemic using pre-trained Word Embedding fastText and GloVe accompanied by the

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CNN-Bi-LSTM architecture, using a common dataset of 40.000 retrieved via Twitter API. Deepak Kumar conducted a test by comparing the two pre-trained Word Embedding. The results obtained in this study with an accuracy of 99.33% for fastText and 97.55% for GloVe [6].

A similar comparison study was conducted by Merinda Lestandy et al. by comparing the Recurrent Neural Network (RNN) and Naïve Bayes Architecture. This study uses the COVID-19 vaccine dataset obtained from the Kaggle repository and the Twitter API. The results obtained in this study with an accuracy of 97.77% for RNN and 80% for Naïve Bayes [7].

The following research that is still related to COVID-19 is by Kazi Nabiul Alam et al., and this study was conducted to determine public sentiment towards the vaccination process. “All COVID-19 Vaccines Tweets” is the dataset used in this study obtained from Kaggle. The selected dataset contains data from almost all well-known vaccines, such as Pfizer/ BioNTech, Oxford/ AstraZeneca, Moderna, Covaxin, Sput nik V, Sinopharm, and Sinovac. Kazi Nabiul Alam, in his research, uses the Deep Learning method with several architectures such as Long Short-Term Memory (LSTM) and Bidirectional LSTM. The results obtained in this study were 90.59% for LSTM and 90.83% for Bi-LSTM [8].

Based on the related studies that have been described, several factors can affect the final performance produced by a method, such as the composition of the dataset and the pre-processing method. However, previous research has focused on the general public's view of the COVID-19 pandemic or COVID-19 vaccination. The focus of this research is to expand the analysis of public sentiment towards some of the government's efforts to break the COVID-19 chain which is divided into four categories such as new normal, social distancing, health protocol fines, and COVID-19 vaccination. Then use, two models are tested and selected for prediction based on the best experimental results involving several models built from Deep Learning Architecture such as Convolutional Neural Network (CNN) and Bidirectional LSTM. Deep Learning architectures are also integrated with one of the pre-trained fastText Word Embedding. A number of the resulting models were trained and tested using self-collected datasets.

The author's purpose in this study using the Deep Learning method is to analyze sentiment regarding the opinion of Indonesian people towards the government's efforts to break the COVID-19 chain so that can determine which government efforts are effective based on the opinions expressed on various social media by the Indonesian people and find out performance and comparison of results obtained from each Deep Learning Architecture.

2. Research Methods

The research method carried out by going through several stages can be seen in Figure 1. The stages begin with collecting data on social media Twitter, YouTube, Facebook, and Instagram, followed by pre-processing the data, then collecting the dataset as training data that is labeled manually, then word embedding, then building the model architecture, followed by the training process and evaluation of the best model using a confusion matrix, then the data prediction process uses the entire collected dataset in addition to training and ends with the visualization process.

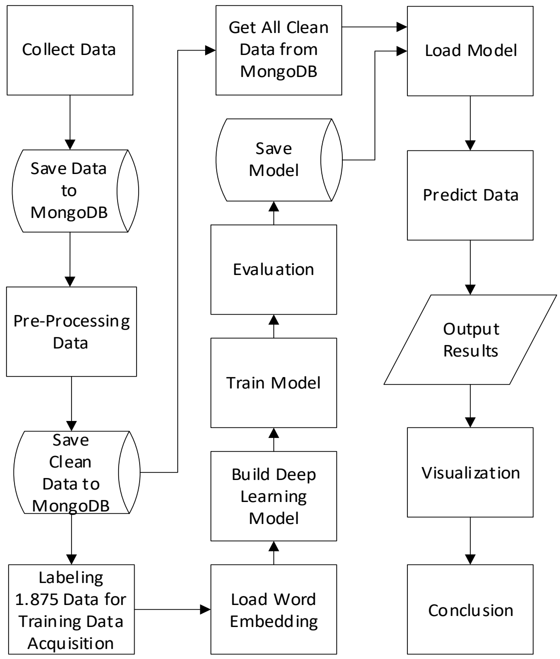

Figure 1. Research Methods

2.1 Collect Data

The data used in this study were collected from social media Twitter, YouTube, Facebook, and Instagram. The data collected is tweet and comment data collected from March 2020 to December 2021, and then the data is stored into MongoDB.

The data is divided into four categories, namely new normal, social distancing, health protocol fines, and COVID-19 vaccinations.

Twitter data collection is done by taking tweet data on Twitter social media using keywords for each category of government efforts to break the COVID-19 chain in Indonesia. The following is the result of collecting Twitter data shown in Table 1.

YouTube data collection is done by taking comment data on YouTube social media using video ids associated with each category of government efforts. The following is the result of collecting YouTube data shown in Table 2.

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Table 1. Collect Twitter Data

Effort Category	Keyword	Amount of Data
New Normal	rapid test, swab test, polymerase chain reaction, #cuciTanganPakaiSabun, #thermogun, thermogun, termogun, #pakaiMasker, hand sanitizer, #disinfektan, disinfektan, #newnormal	191.576
Social Distancing	#psbb, psbb, #ppkm, ppkm, #socialDistancing, social distancing, #sosialDistancing, sosial distancing, #physicalDistancing, physical distancing, jaga jarak, #dirumahSaja, dirumahSaja, #dirumahAja, dirumahAja, wfh, #isolasiMandiri, isolasi mandiri	943.523
Health Protocol Fines	#dendaMasker, denda masker, #raziaMasker, razia masker, denda protokol kesehatan	61.231
COVID-19 Vaccinations	#vaksin, vaksin, vaksin covid, #vaksinCorona, vaksin corona	1.253.503

Table 2. Collect YouTube Data

Effort Category	Amount of Data
New Normal	12.749
Social Distancing	5.010
Health Protocol Fines	27.139
COVID-19 Vaccinations	15.054

Facebook data collection is done by taking comment data on Facebook social media using post ids related to each category of government efforts. The following is the result of collecting Facebook data shown in Table 3.

Table 3. Collect Facebook Data

Effort Category	Amount of Data
New Normal	22.449
Social Distancing	12.524
Health Protocol Fines	14.428
COVID-19 Vaccinations	40.984

Instagram data collection is done by taking comment data on Instagram social media using post ids related to each category of government efforts. The result of collecting Instagram data shown in Table 4.

Table 4. Collect Instagram Data

Effort Category	Amount of Data
New Normal	7.281
Social Distancing	25.403
Health Protocol Fines	4.402
COVID-19 Vaccinations	3.568

2.2 Pre-Processing Data

Pre-Processing Data is a process to convert text data into a more understandable form. Pre-Processing is helps to find relationships between data and extracting features for data so that the data is ready to be processed and studied [9]. The processes carried out at the pre-processing stage are cleansing, case folding, tokenization, text normalization, stopword removal, and stemming.

The first stage is cleansing. Cleansing is the process of correcting or removing poor-quality data from the database. This process is carried out to ensure the best data quality by eliminating poor quality data [10], besides being useful for getting the best data quality, it also serves to reduce the processing load [11]. The results of a cleansing stage can be seen in Figure 2.

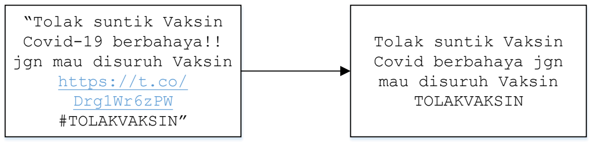

Figure 2. Cleansing

The second stage is case folding. Case folding is the process of converting all letters in text or word tokens into lowercase or uppercase, but lowercase is more commonly used in this process [12]. Results from the previous stages are processed for case folding, as shown in Figure 3.

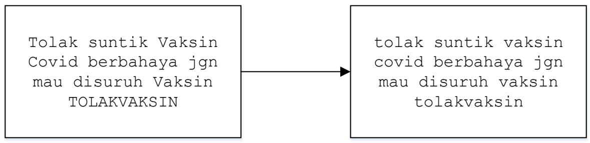

Figure 3. Case Folding

The third stage is tokenization. Tokenization is the process of dividing a text into word tokens, where words are the smallest text components that still have meaning. Processing at the text level is more complicated than processing at the word level [13]. Tokenization relies on space characters in sentences to separate words [14]. Results from the previous stages are processed for tokenization, as shown in Figure 4.

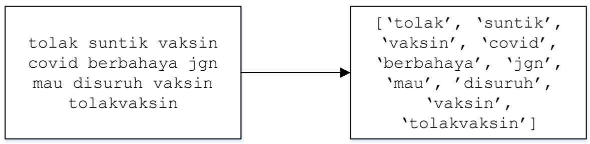

Figure 4. Tokenization

The fourth stage is text normalization. Text normalization is the process of converting non-standard/ slang words in a text into general words [15]. Text normalization can help to parse language to understand the meaning better, and language processing performance can be improved by normalizing words [16]. Words will be checked one by one, and if there are words not standard/ slang and contained in the corpus colloquial, then the word will be replaced with the actual word. The text normalization process in Indonesian uses the lexicon colloquial-indonesian-

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lexicon.csv [16]. The results of the previous stages are processed for text normalization, as shown in Figure 5.

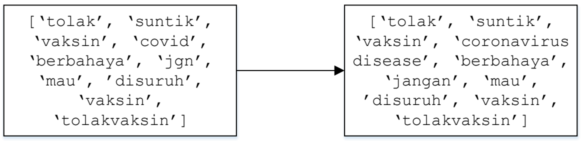

Figure 5. Text Normalization

The fifth stage is stopword removal. Stopword removal is the process of removing stopwords or words that often appear but have no meaning, such as prepositions, articles, or pronouns [17]. This process has an impact on reducing the size of the vocabulary so that the computational process becomes lighter. The results from the previous stages are processed for stopword removal, as shown in Figure 6.

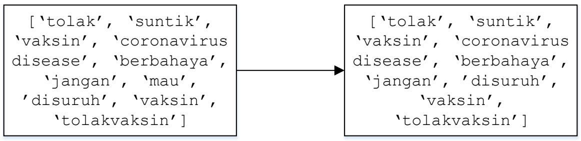

Figure 6. Stopword Removal

The last stage is stemming. Stemming is the process of changing a formed word into a basic word. The stemming process is very dependent on the language of the word to be processed [18]. This is because the stemming process must apply the morphological rules of a language, where Indonesian has more complex affixes [19]. The results from the previous stages are processed for stemming, as shown in Figure 7.

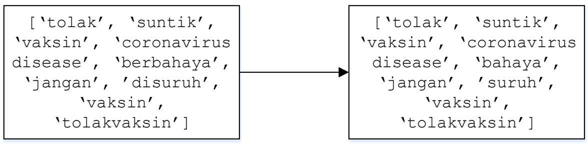

Figure 7. Stemming

2.3 Dataset Labeling

Data that has been through the pre-processing stage will be used as much as 1.875 data as training data which comes from data collected on each social media [20]. The training data will then be labeled with a manual approach based on positive, negative, and neutral classes. The manual labeling approach was chosen in order to be able to know every progress to get good data quality according to the problems raised because the labeling process is done manually, so there are limited resources such as energy and time. Training data as much as 1.875 data is used to carry out the training process in building a Deep Learning model. Research [21] and [22] conducted research with 630 small training datasets on neural networks getting 98.3% accuracy. The results of the sentiment labels are shown in Table 5.

Table 5. Sentiment Label

Text	Sentiment
wajib pakai masker pakaimasker jagajarak cucitangan	positive
sakit tolol swab tes	negative
semprot disinfektan rumah hahaha	neutral

2.4 Word Embedding

Word Embedding or distributed word representation is a technique that maps words in vocabulary into vector numbers [23]. The advantage of word embedding is that it can reduce word vector dimensions and improve computational performance [24]. Vector of numbers obtained when visualized shows the closeness between words with the same meaning [25]. Word embedding can do this because word embedding can capture the semantic and syntactic information of a word in a large corpus [26]. Word embedding can be created directly from the existing dataset or using pre-trained word embedding that is already available.

fastText is a pre-trained word embedding developed by Facebook AI Research. The way fastText works in obtaining a vector representation of a word is similar to Word2Vec [27]. In particular, fastText can handle new out-of-vocabulary (OOV) terms. fastText tries to add subword information using Bag of Character N-grams by calculating the average vector representation of n-grams. Adding subword information to word embedding also has a good impact on vector results for words that rarely appear or are misspelled [28][29].

2.5 Deep Learning

Deep Learning utilizes artificial neural networks to implement problems with large datasets [30]. Deep Learning can perform feature extraction automatically because it consists of layers such as a convolutional layer, pooling layer, and fully connected layer [31][32]. In this study, the author uses the Deep Learning Method with two different architectures tested to determine which architecture has the best performance. The combination of layers used in both architectures results from studies from previous research [30]. Then the author of this study added a dropout layer which functions to pass through several neurons in the hidden layer to reduce the level of complexity in order to prevent overfitting.

Convolutional Neural Network (CNN) is a DNN architecture used to process data in the form of a grid [33]. CNN consists of convolution layers whose function is to map the characteristics of the input data through it. Convolution layers are arranged by applying different filter sizes to produce different feature mappings [34]. Can be seen in Figure 8. One input layer with 100-dimensional is connected to the embedding layer, and this study uses a pre-trained Indonesian fastText embedding with 300 dimensions. The embedding layer will be connected to three one-

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dimensional convolution layers with different kernel sizes, where each convolution layer will produce a different feature mapping. Each convolution layer will be connected to the max-pooling layer to compress features and control overfitting. A concatenate layer will combine the features obtained from each max-pooling layer. The concatenate layer is then connected with two convolution layers and a max-pooling layer for further feature extraction. Finally, the global max-pooling layer is connected to the fully connected layer, the dropout layer to reduce the number of neurons, and the output layer.

Figure 8. CNN Architecture [30]

Bidirectional LSTM is a Recurrent Neural Network (RNN) architecture with a memory block consisting of two Long Short-Term Memory (LSTM) that are in opposite directions and connected to the output layer. This architecture can enhance the memory capabilities of the LSTM by providing past and future context information for each point in the input layer [35][36]. Figure 9 describes the Bidirectional LSTM architecture used in this study, where there is a 100-dimensional input layer followed by an embedding layer where the weight is taken from a pre-trained Indonesian fastText with 300 dimensions and is connected in a Bidirectional LSTM layer. Next, the global max-pooling layer is one-dimensional, the fully connected layer, the dropout layer to reduce the number of neurons, and the output layer predicts the class.

2.6 Evaluation

CNN and Bidirectional LSTM models were evaluated with performance measurements such as accuracy, precision, recall, and F1-score using the Confusion Matrix. Accuracy is the ratio of the number of correct predictions to the total number of test data [37][38]. The equation used to calculate accuracy can be seen in Equation 1.

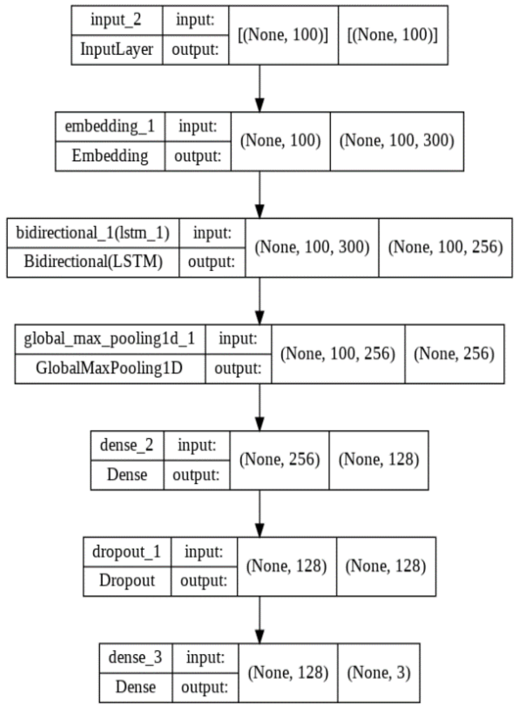

Figure 9. Bidirectional LSTM Architecture [30]

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

Precision is the amount of data in the positive class that is correctly predicted (true positive) from the overall positive predicted data [37][38]. The calculation of precision can be seen in Equation 2.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall is the ratio of the number of correct predictions in the positive class to the total data in the positive class [37][38]. The recall calculation can be seen in Equation 3.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

F1-score, also known as F-measure, is a measurement method that represents the average harmonic value (harmonic mean) between recall and precision values [37][38]. The F1-score calculation can be seen in Equation 4.

$$F1-score = 2\ x\ \frac{Precision\ x\ Recall}{Precision+Recall} \quad (4)$$

To evaluate the hyperparameters on the test using tables and visualizations in the form of bar plots. The hyperparameters tested are filters/units, batch size, dropout, and optimizer. There are seven optimizer methods tested, namely SGD, RMSprop, Adam, Adadelta, Adagrad, Adamax, and Nadam.

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3. Results and Discussions

The Deep Learning method is used with the python programming language and the help of pre-trained word embedding fastText as feature extraction. The research equipment used includes an Intel Core i7-7700HQ CPU, NVIDIA GeForce GTX 1050, and 16 GB of RAM. To ensure the successful performance of the proposed model, the evaluation procedures carried out include training datasets, model evaluations, and score metrics.

3.1 Training Dataset

The training dataset is used to train the Deep Learning model that has been built. Tests in this study used two different architectural models trained with 1.875 training datasets that had gone through the pre-processing stage and were labeled manually. The number of training dataset samples is 1.875 data taken based on the division of each category of effort on each social media, sentiment classes are positive, negative, neutral, and time constraints in the study. The distribution of training datasets can be seen in Table 6.

The 1.875 training dataset is considered sufficient to train the Deep Learning model because, in this study, the vocabulary processing process uses pre-trained word embedding so that the resulting vector represents the word well and facilitates the feature extraction process.

Table 6. Sentiment Label Distribution

Effort Category	Positive	Negative	Neutral	Total Data
New Normal	156	156	156	468
Social Distancing	157	157	157	471
Health Protocol Fines	156	156	156	468
COVID-19 Vaccinations	156	156	156	468

3.2 Model Evaluation

The model testing begins with setting the hyperparameter values, namely filters/units, batch size, dropout, and optimizer method. The final results of hyperparameter testing on CNN Architecture and Bidirectional LSTM can be seen in Tables 7 and 8.

Testing of seven optimizer methods, namely SGD, RMSprop, Adam, Adadelta, Adagrad, Adamax, and Nadam, can be seen in Figures 10 and 11.

The bar plot visualization in Figure 10 and Figure 11 shows that testing the optimizer method on each architecture got the best results on the Nadam Optimizer based on the accuracy values obtained for both architectures.

Testing on the test size is also carried out to determine the performance obtained by the model during training. The test sizes that were tested consecutive 20%, 30%, 40%, and 50% on each architecture can be seen in Table 9 and Table 10.

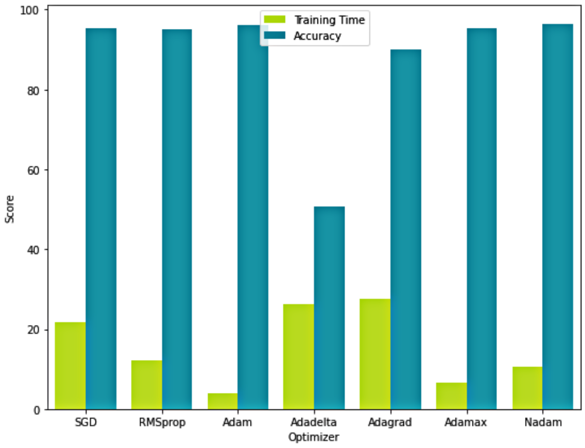

Figure 10. CNN Architecture Optimizer Testing

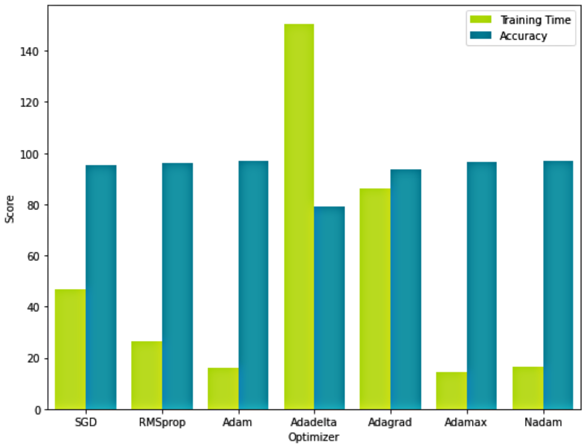

Figure 11. Bidirectional LSTM Architecture Optimizer Testing

Table 7. CNN Architecture Hyperparameter

Parameter	Score
Filters	16
Batch Size	128
Dropout	0.2
Optimizer	Nadam

Table 8. Bidirectional LSTM Architecture Hyperparameter

Parameter	Score
Units	128
Batch Size	64
Dropout	0.3
Optimizer	Nadam

Table 9. CNN Architecture Test Size

Test Size	Accuracy	Precision	Recall	F1-Score
0.2	**0.944000**	**0.943928**	**0.944000**	**0.943933**
0.3	0.879218	0.878951	0.879139	0.878524
0.4	0.822667	0.822395	0.822667	0.821806
0.5	0.815368	0.820510	0.815447	0.814426

Table 10. Bidirectional LSTM Architecture Test Size

Test Size	Accuracy	Precision	Recall	F1-Score
0.2	**0.973334**	**0.973331**	**0.973333**	**0.973331**
0.3	0.920071	0.923478	0.920023	0.920373
0.4	0.902666	0.902698	0.902667	0.902275
0.5	0.844184	0.857937	0.844276	0.843968

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Comparison of CNN and Bidirectional LSTM Architecture results evaluated from accuracy, precision, recall, and F1-score results. The Confusion Matrix was used to assess the performance of each model shown in Figure 12 and Figure 13.

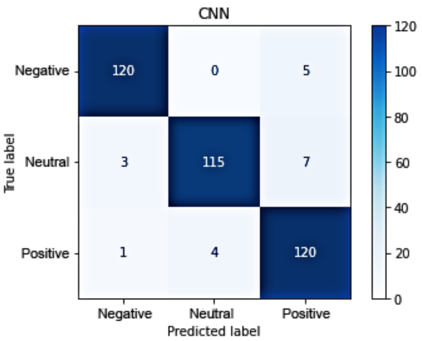

Figure 12. Confusion Matrix CNN

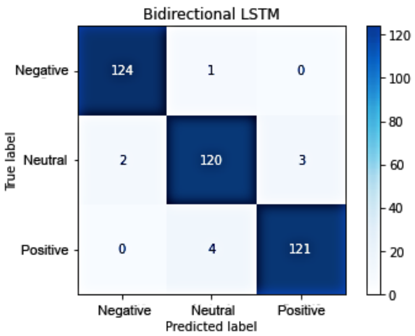

Figure 13. Confusion Matrix Bidirectional LSTM

Table 11 shows that the Bidirectional LSTM Architecture was able to obtain a value of 97.34% for accuracy, 97.33% for precision, 97.33% for recall, and 97.33% for F1-score, which was superior to CNN Architecture with a value of 94.40% for accuracy, 94.39% for precision, 94.40 % for recall, and 94.39 for F1-score. There are differences in the results obtained with a similar architecture in the Bidirectional LSTM accuracy value [8] of 90.83%.

CNN architecture excels in training time, 86.49/sec, and for Bidirectional LSTM Architecture, 151.82/sec. Bidirectional LSTM has an LSTM layer in two directions, where the first LSTM will predict from the past to the future and the second LSTM predicts from the future to the past so that when the training process occurs, Bidirectional LSTM architecture requires a longer training time, which is 151.82/sec compared to with CNN which takes 86.49/sec. The combination of pre-trained word embedding fastText 300 dimensions in Indonesian with 2.000.000 tokens gives excellent results.

Table 11. Comparison of CNN Architecture and Bidirectional LSTM

Architecture	Accuracy	Training Time/sec
CNN	0.944000	86.49
Bidirectional LSTM	0.973334	151.82

3.3 Prediction and Visualization

The prediction process uses all unlabeled classification data that has been collected on each social media and has been pre-processed. The classification model of the Bidirectional LSTM was chosen because it obtained a higher value than CNN. Sentiment prediction results are classified into three classes, namely positive, negative, and neutral sentiment. Prediction results are then visualized using Tableau.

Visualization of the amount of data on social media Twitter, YouTube, Facebook, and Instagram based on four categories of government efforts to break the COVID-19 chain in Indonesia in the form of a bar chart is shown in Figure 14.

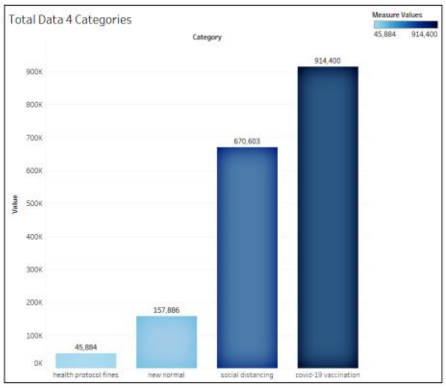

Figure 14. Total Data 4 Categories

Visualization of line chart showing a trend of effort category per month. Figure 15 shows the visualization of positive data. There is an increase in initial data in the category of social distancing in February 2021. There is a significant increase in July 2021 to 100.087 data, as reported by Kontan.co.id this shows the relevant results where the amount of social assistance from the government received by the community during the implementation of restrictions on community activities [39], followed by the COVID-19 vaccination category which increased in March 2021 to 32.713 data, reported by liputan6.com this shows the relevant results where in March the number of recipients of the first and second doses of the COVID-19 vaccine increased by hundreds of thousands of souls [40].

The following visualization in Figure 16 shows a visualization for negative data, which experienced an increase in initial data in the social distancing category in June 2021. There was a significant increase in data that occurred in July 2021 to 103.058 data, reported from kominfo.go.id. This shows a relevant result where the government decided to enforce the policy of Restrictions on Emergency Community Activities from July 3 to July 20, 2021 [41], followed in second place by the COVID-19 vaccination category, which increased in July 2021 to 47.479 data, reported from covid19.go.id this shows the relevant results where on

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July 16, 2021, a video of the potential dangers of COVID-19 vaccination and the viciousness of the virus after vaccination has circulated and previously on March 7, 2021, the same video has also circulated containing a chain message video of the potential dangers of the COVID-19 vaccine [42]. Figure 17 is a visualization for neutral data, which experienced an increase in initial data in the COVID-19 vaccination category in March 2021. There was a significant increase in July 2021 to 164.717 data, followed by the second position with the category of social distancing, which increased in July 2021 to 80.803 data.

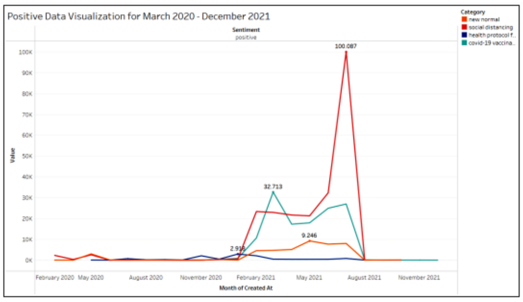

Figure 15. Positive Data Visualization

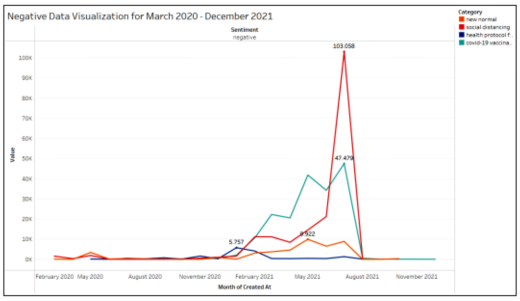

Figure 16. Negative Data Visualization

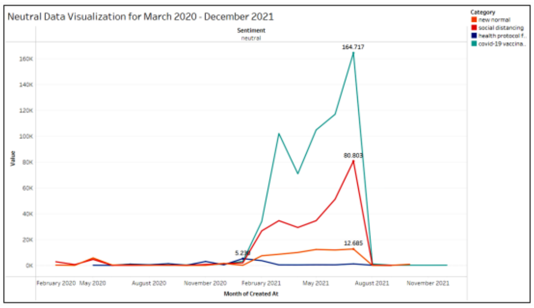

Figure 17. Neutral Data Visualization

The pie chart visualization of the four categories is made in the form of a dashboard, and the percentage of each category is calculated. Figure 18 shows that the social distancing category has the highest positive sentiment value compared to other categories of 33.93%, for the health protocol fine category has the highest negative sentiment value compared to other categories of 35.64%, while the COVID-19 vaccination category has the highest neutral sentiment value of 65.74%.

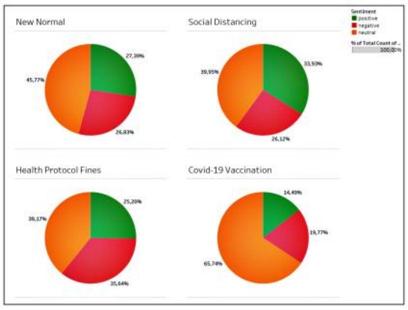

Figure 18. Comparison of Four Categories

A word cloud visualization shows the most discussed words sorted from small to large based on how often each word occurs. This study displays a filtered word cloud visualization based on the 200 most discussed words. The visualization of the positive sentiment word cloud is shown in Figure 19.

Figure 19. Positive Sentiment Word Cloud

The negative sentiment word cloud visualization filtered based on the 200 most discussed words is shown in Figure 20.

Figure 20. Negative Sentiment Word Cloud

The neutral sentiment word cloud visualization filtered based on the 200 most discussed words is shown in Figure 21.

Figure 21. Neutral Sentiment Word Cloud

4. Conclusion

The process of analyzing public sentiment towards the government's efforts to break the COVID-19 chain in Indonesia consists of 5 stages, including the process of collecting data, pre-processing data, training model, evaluation, predicting data, and data visualization. The process of collecting data is carried out by taking data from public opinion posts on Twitter, YouTube, Facebook, and Instagram.

This study used 1.875 training datasets to train a Deep Learning model combined with pre-trained word embeddings fastText. The performance of each Deep Learning Method in predicting public sentiment toward the government's efforts to break the chain of COVID-19 is quite diverse. The CNN architecture can achieve the best performance of 94.40% for accuracy, 94.39% for precision, 94.40% for recall, and 94.39% for F1-score, while the LSTM Bidirectional Architecture can achieve the best performance of 97.34% for accuracy, 97.31% for precision, 97.33% for recall, and 97.31% for F1-score. The Bidirectional LSTM architecture has a better value compared to the CNN Architecture because the Bidirectional LSTM has a long-short term memory block that works both ways so that the knowledge of the information possessed is very much, coupled with the presence of a forget gate on the LSTM helps to determine the information that is still feasible to be retained on the memory block.

Comparison of classification results using the Bidirectional LSTM model on public sentiment regarding the government's efforts to break the COVID-19 chain in Indonesia based on the visualization results on Tableau shows that in the overall classification data, the social distancing category is considered the most effective effort by the community by having the highest positive sentiment value of 33.93%, while for efforts that are considered less effective, it is in the category health protocol fines for having the highest negative sentiment with a value of 35.64%. Based on the classification results, the effort recommended for the government is to implement social distancing in each zone of the region with a level that is by the cases in the regional zone because the Corona Virus is a virus that is very easily transmitted even through tiny droplets such as fluids released when a person coughs or sneezes, the implementation of social distancing can prevent the spread of the disease in certain areas, as can be seen in the data on COVID-19 cases in Indonesia also shows that the implementation of social distancing can reduce COVID-19 cases drastically. Meanwhile, the implementation of health protocol fines in the form of administrative fines should be dismissed or optimized because of polemics in the community that tend to be contrary to the implementation of health protocol fines. Because of this, the community causes a sense of hatred and demands justice so that it has an impact on ignoring health protocols, as can be reported in Kompas.id shows that COVID-19 cases in Indonesia are increasing due to lack of compliance people against health protocols [43].

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