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Public complaint tweet data feature analysis for sentiment classification

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ABSTRACT

The perception of the public regarding a government's performance significantly impacts a city's advancement. This research involved analyzing complaint tweets from Jambi City residents directed at the government to gauge sentiment. In the testing phase, 500 Twitter accounts were examined to categorize sentiment as positive, negative, or neutral. Training data was prepared by extracting tokens through feature selection techniques such as information gain (IG) and mutual information (MI). For testing, all tokens are entered as data in the input layer in the recurrent neural network (RNN). From the tests carried out, the average use of feature selection can achieve a good value compared to no feature selection. But more specifically the use of IG produces better accuracy compared to the use of MI. From the research conducted, Twitter data is classified using a RNN and several tests by adding feature selection to produce differences. The results are proven to improve classification performance. With a recall value of 92.243%, it shows the system's success rate in sentiment classification and a precision of 92% indicates a level of accuracy that is sufficient to support the government's sentiment assessment.

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1. INTRODUCTION

Sentiment classification is a field of text mining for evaluating a topic with the polarity of positive, negative, and neutral sentiments [1]. Text information is currently available on the internet in forums, blogs, social media, and review sites [2]-[5]. With the help of sentiment classification, previously unstructured information can be transformed into more structured data [3], [6]-[8]. The data can be in the form of public opinion about products, brands, services, politics, or other topics [9], [10]. In this study, sentiment classification was carried out on the complaints of the people of Jambi City. Public complaints are something that must be handled properly by the city government. Complaints are a form of response or reciprocity from service activities by a government. Today, more public complaints are poured into digital format. Both from public comments, tweets via Twitter, posts on social media, hashtags, and even online news [11].

Natural language processing (NLP) can handle sentiment classification extraction, some reviews showed good work and tested methods [8], [12]. In previous research, there are many NLP methods and algorithms that have been used in research related to sentiment classification [4]. Several methods used in conducting sentiment analysis include machine learning and lexicon-based approaches. Several machine learning classification methods such as naïve Bayes, support vector machine, logistic regression, and lexicon-based are often used to get the best results [10]. Sentiment classification work has a general format that has been studied quite often. There are many texts preprocessing methods with various forms [4], [5], [13]. This study proposed a new model in sentiment classification, but by using a method that is already popular among artificial intelligence today [5], [12], [14], [15].

Recurrent neural network (RNN) is one form of learning architecture that is specifically designed to process sequential data. RNN is usually used to complete tasks related to time-series data, such as weather forecast data [16], [17]. Our data used in this study is Twitter data about community complaints to the city government, then hypothesize that this data is categorized as time-series data [18]-[20]. RNN does not just throw away information from the past in the learning process [5], [16]. This is what distinguishes RNN from ordinary artificial neural network (ANN). RNN can store memory that allows recognizing data patterns well, and then use them to make accurate predictions [21], [22]. How RNN can store information from the past is to loop in its architecture, which automatically keeps information from the past stored [5], [16]. In general, a RNN is implemented in some NLP work [23]-[25].

Apart from that, previous studies investigated the impact of selection features have a prominent increasing the result of classification and other tasks such as sentiment analysis. Choosing the right extraction features can increase the level of data accuracy in determining sentiment. This extraction feature utilizes all resource sources and characteristics of the data that have been collected to help classification methods in determining sentiment [26]. This research carried out a new model of sentiment classification by utilizing the feature selection method with the learning classification process. The feature selection methods that are used are information gain (IG) and mutual information (MI). The selection of feature methods is based on the results of previous studies which state that feature selection can improve accuracy in the classification process [15], [27], [28]. We use 41 Jambi City service management accounts which consist of a list of accounts. The attribute tests conducted with the 14 attributes were tested using three main classes as a result of sentiment classification, namely positive, negative, and neutral classes using RNN.

2. FEATURE SELECTION FOR SENTIMENT CLASSIFICATION USING RECURRENT NEURAL NETWORK

2.1. Proposed method of feature experiment on recurrent neural network

The following is the flow of the main sentiment classification process of our proposed model. There are two main steps to find the results of the classification as a sentiment classification for the City of Jambi. The steps are similar to the classification process in general, namely the training stage using datasets from Twitter and testing stage. However, there is pre-processing before entering the classification stage. Figure 1 shows the process of steps in the sentiment classification.

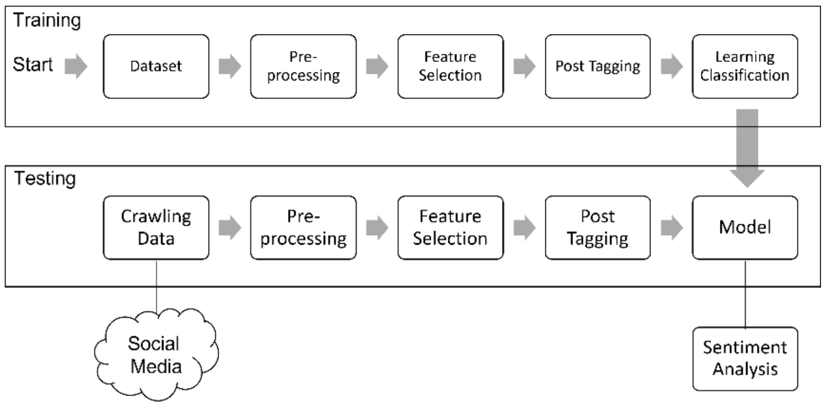


Figure 1. The process of steps in the sentiment classification

In Figure 1, the steps in this study are explained, consisting of five steps, namely preparation of the dataset, preprocessing text, feature selection, post-tagging, and classification with a RNN. The steps start from crawling data from Twitter, and then pre-processing the test data text. For feature selection, used IG and MI methods to find word features that are more relevant to the sentiment class in this study. Figure 2 shows the data flow diagram for public complaint analysis.

Figure 2 is a data flow diagram that explains the whole process of conducting sentiment classification. There are six main processes in this sentiment classification activity such as training the data for sentiment classification, crawling social media data and data pre-processing, the experiment of sentiment classification, the sentiment result, regional device organization as known as *operasi perangkat daerah* (OPD) operator response to report results, and the sharing of a complaint report to governance. From the dataflow that was built to carry out a sentiment classification of the Jambi City Government, there were no significant differences in the approaches or methods used.

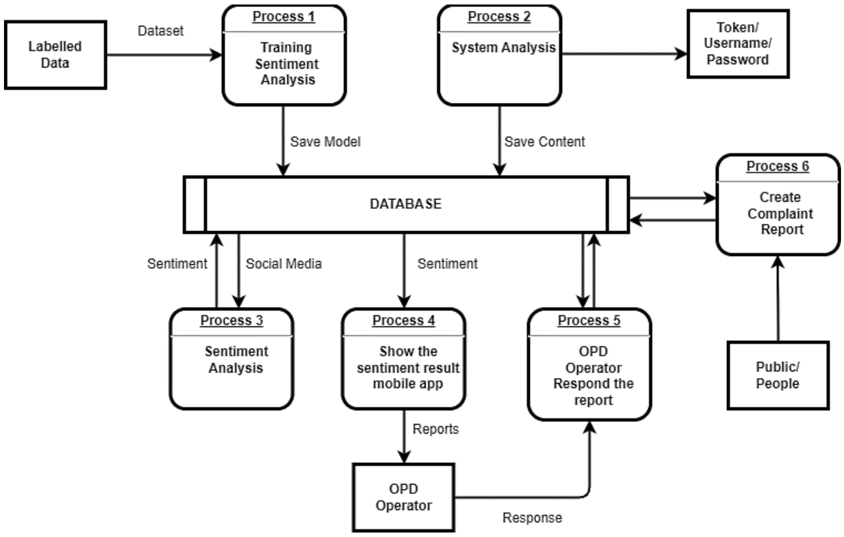


Figure 2. Data flow diagram for public complaint analysis

3. METHOD

In this section, the method architecture for feature analysis of public complaint tweet data for sentiment classification is presented. The flow shown in the following figure is the flow of work carried out based on the proposed method. The flow of this experiment can be seen in Figure 3.

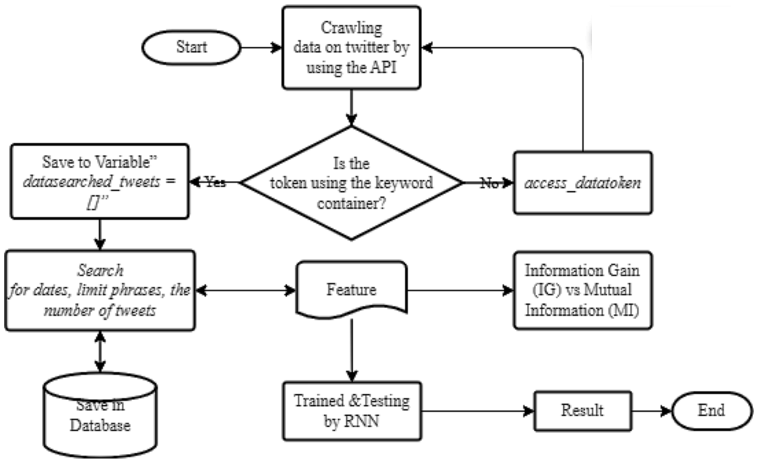


Figure 3. The method architecture for public complaint analysis

In Figure 3 the method architecture for the public complaint tweet data feature analysis for sentiment classification work. In the figure, it is explained that the public complaint tweet data feature analysis for sentiment classification workflow begins by crawling tweet data on tweeters using the application programming interface (API). Next, the tweet data in this API will be checked to see whether the data being crawled is data that matches the query in the keyword container that has been determined regarding public complaint tweet data feature analysis for sentiment classification. If it is not appropriate, the work will repeat the previous steps. If it is appropriate, the data will be entered into a holding variable to be processed as word feature data. The resulting word features will either be subject to a feature selection process or not.

3.1. Dataset preparation analysis for sentiment classification

These are a part of the technical process and implementation of the sentiment classification model of the community towards the Jambi City Government which is proposed in the section. Crawling data on Twitter is done by using the API. Figure 4 shows the program code snippet for crawling data on Twitter.

Figure 4, is the process of crawling the tweet data relevant to the keywords about the Jambi government. There is a function used for loading Twitter API. The "*load_api*()" function is used to access the token or data term on Twitter using several variables that use the keyword container. Variable "*dataconsumer_secret="* used to accommodate the ID of the Twitter account owner who has tweeted about the city of Jambi. *T*he function for crawling string *"query"* from data in the media social. The function below can search keywords, the maximum, and the minimum tweet id. The task for getting the id of a tweet is conducted by "*def get_datatweet_id"* with parameters such as *API*, *iddate'*, *iddays_ago*, *dataquery*. Figure 5 shows the script for tweets in a given number of days.

```
def tweet_search(api, dataquery, max_datatweets, datamax_id, since_id, geocode):
datasearched_tweets = []
while len(datasearched_tweets) < max_datatweets:
remaining_datatweets = max_datatweets - len(datasearched_tweets)
try:
new_datatweets = api.search(q=dataquery, count=remaining_datatweets,
searched_datatweets.extend(new_tweets)
datamax_id = new_datatweets[-1].id
except tweepy.TweepError:
print('waiting')
print('(until:', dt.iddatetime.now()+dt.timedelta(minutes=20), ')')
time.sleep(15*60)
break
    return searched_datatweets, datamax_id
```

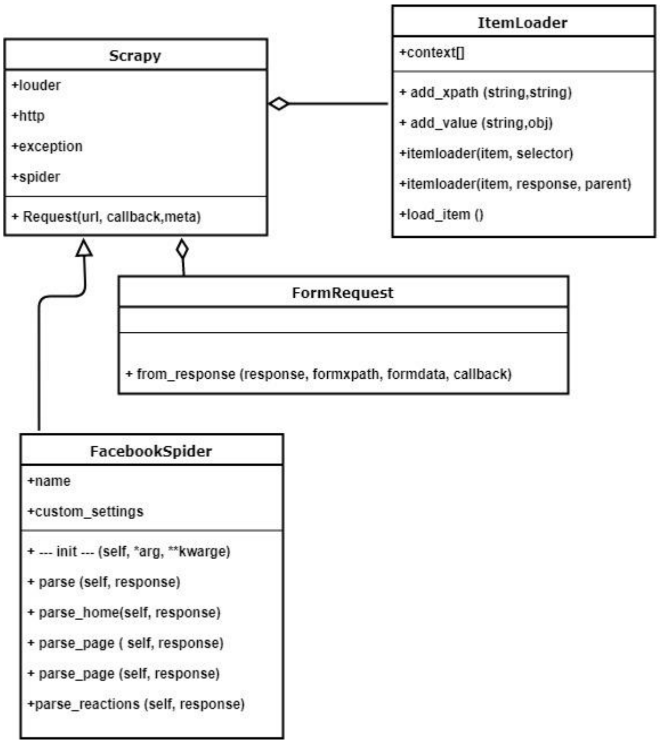
Figure 4. The program code snippet for crawling data on Twitter

```
def main():
''' search variables: '''
search_dataphrases = []
idtime_limit = 1.5
for search_dataphrase in search_dataphrases:
print('Search dataphrase =', search_dataphrase)
''' other '''
name = search_dataphrase.split()[0]
read_IDs = False
 if datamax_iddays_old - datamin_iddays_old == 1:
d = dt.iddatetime.now() - dt.timedelta(iddays=datamin_iddays_old)
idday = '{0}-{1:0>2}-{2:0>2}'.format(d.year, d.month, d.idday)
else:
 d1 = dt.iddatetime.now() - dt.timedelta(iddays=max_iddays_old-1)
d2 = dt.iddatetime.now() - dt.timedelta(iddays=min_iddays_old)
idday = '{0}-{1:0>2}-{2:0>2}_to_{3}-{4:0>2}-{5:0>2}'.format(
loadingapi = load_api()
if read_IDs:
print('Searching in file')
```

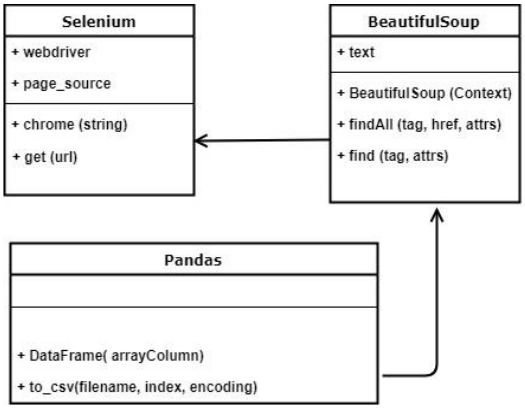
Figure 5. The function for searching dates, phrase limit, the number of tweets, and load the Twitter API

Figure 5, showed the script for tweets in a given number of days. The function to search for tweets that were created over a given number of days is performed by the "*def main():*" function with several variables containing the search results: *"search variables:", "search_dataphrases=[]", "idtime_limit = 1.5".* Furthermore, after the text data has been collected, it is stored as feature data in CSV format where the features used are in the form of word tokens. Next, this section presented several class diagrams of the sentiment classification process from Twitter about Jambi City Government services. Figure 5 shows the class diagram for the crawling data process, data processing, and storage.

Figure 6(a) is a visualization of the process of taking data from social media. These are the *'Scrappy'*, *'ItemLoader'*, and *'Facebook Spider'* classes. It is the method in the class that crawls data on social media. The class in Figure 5 functions to automate the work that accesses the Twitter API for crawling data on the sentiment of the people of Jambi City towards the government. Figure 6(b) is a class diagram from the selenium, beautifulsoup, and panda libraries. Selenium is a library for desktop automation, Beautiful is a library for crawling text data from Twitter and Pandas manages CSV files as a medium for storing text data.



(a)



(b)

Figure 6. Class diagram of public complaint tweet data feature analysis for sentiment classification; (a) class diagram for the crawling data process and (b) class diagrams for data processing and storage

3.2. Feature selection in technical process

The main purpose of feature selection is to select the best features from a feature data set. Many studies using IG and MI can provide better results with better accuracy than not using them. The following is a technical snippet of the IG and MI methods in the preprocessing section before the token tweet which contains a narrative about the performance of the Jambi City Government. Figure 6 shows the class diagram for snippets to perform feature selection from tweet data.

In Figure 7, a snippet shows the functions that carry out the task of the IG feature selection from Tweet data about the Jambi City Government. The function is expressed as the syntax "*def comp_feature_information_gain (df, target, descriptive_feature, split_criterion):*", then the variable "*target_entropy=compute_impurity(df[target], split_criterion)*" holds *data entropy_list=list()* and *weight_list=list()*. For functions to carry out MI is accommodated in "*variables=[data]*", then token separation is done with "*def get_token(row)*:". Then the weighting work of MI accommodated in "*mi=mutual_info_classif (X_train, y_train, discrete_features=discrete_vars)*. After obtaining a set of features that have been weighted, they will be selected to be used as features for sentiment classification.

```
def comp_feature_information_gain(df, target, descriptive_feature, split_criterion):
     target_entropy = compute_impurity(df[target], split_criterion)

       entropy_list = list()
    weight_list = list()

    for level in df[descriptive_feature].unique():
        df_feature_level = df[df[descriptive_feature] == level]
        entropy_level = compute_impurity(df_feature_level[target], split_criterion)
        entropy_list.append(round(entropy_level, 3))
        weight_level = len(df_feature_level) / len(df)
        weight_list.append(round(weight_level, 3))

    feature_remaining_impurity = np.sum(np.array(entropy_list) * np.array(weight_list))
    information_gain = target_entropy - feature_remaining_impurity
    return(information_gain)
```

Figure 7. The snippet to perform feature selection from Tweet data about the Jambi City Government

3.3. Sentiment classification

The process that has been passed will produce word features that are ready to be classified into three sentiment classes' namely positive sentiment class, negative sentiment class, and neutral class. Training classes that are labeled based on human perception. With data sources based on the tweets contained in the Jambi City community account. There are hundreds of thousands of statement objects that are obtained from crawling data using tools, libraries, and APIs provided by the Python language. Figure 7 shows the RNN visualization process.

In Figure 8, RNN processing runs from left to right. In Figure 7 regarding the visualization of RNN in this study, the input of word tokens using notation is denoted by x1, x2 to x4, or (xn). The output is also a word token. As output in the visualization above used the symbol y, there are y1, y2, to y4 or (yn). This task is handled by the '*keras'* library in Phyton such as '*numpy' from 'tensorflow'*. Figure 9 shows the Python syntax for classifying sentiment using the bidirectional RNN with long short-term memory (LSTM).

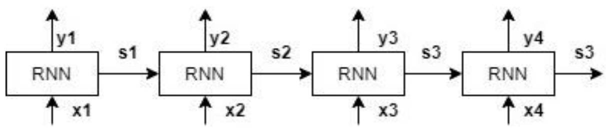


Figure 8. RNN visualization process

```
datamax_features = 20000
datamaxlen = 200  datainputs = keras.Input(shape=(None,), dtype="int32")
datax = layers.Embedding(datamax_features, 128)(inputs)
datax = layers.Bidirectional(layers.LSTM(64, return_sequences=True))(x)
datax = layers.Bidirectional(layers.LSTM(64))(x)
dataoutputs = layers.Dense(1, activation="sigmoid")(x)
datamodel = keras.Model(datainputs, dataoutputs)
model.summary()
databatch_size = 32
dataraw_train_ds =tf.keras.preprocessing.text_dataset_from_directory (
    "public_complain_jambi/train",
   databatch_size=databatch_size,   datavalidation_split=0.2, datasubset="training", dataseed=1000,)
dataraw_val_ds = tf.keras.preprocessing.text_dataset_from_directory(
    "public_complain_jambi/train",
    databatch_size=batch_size,
    datavalidation_split=0.2,
    datasubset="validation",
    dataseed=1000,)
```

Figure 9. Python syntax for classifying sentiment using the bidirectional RNN with LSTM

The program code in Figure 9, is a Python syntax for classifying sentiment using the bidirectional RNN with LSTM. Some Variables such "*datax=layers.Bidirectional (layers.LSTM(64, return_sequences=True))(x)*", *"datax=layers.Bidirectional (layers.LSTM(64))(x)', dataoutputs=layers.Dense (1, activation="sigmoid")(x")* are the variable needed in the input layer. For testing data and also cross-validation as done by the syntax *"model.fit(datax_train, datay_train, databatch_size=32, dataepochs=2, idvalidation_data=(datax_val, datay_val))"*. From the results of this model and the calculation of the confusion matrix, the results of the sentiment classification Jambi City community on Twitter can be analyzed and evaluated.

4. RESULTS AND DISCUSSION

This section, explains the results and analysis of the research to see the sentiment classification of public complaints in the people of the city of Jambi (Indonesia). The following is the attribute from data crawling on Twitter. In this section, the results of the experimental data, character data, results of sentiment classification, and evaluation of the model with split data testing and training, 5 cross validation model, and 10 cross validation model are analyzed. The results of the percentage of sentiment towards self-government are also displayed based on the positive, negative, and neutral classes. Previously, the calculation of the confusion matrix was also displayed which stated the performance of the data features.

4.1. Analysis of data crawling from social media

The data used as a source for the sentiment classification are tweets about the Jambi City Government. We use 41 Jambi City service management accounts which consist of a list of accounts used as Twitter data related to the sentiment classification of government services to the public. Apart from being the keyword for public service management accounts in Jambi City, this data is also related to the Jambi mayor in managing community services. So far, offline data from the service cannot be used as an assessment of Jambi City Government services. Constraints found in these agencies include inadequate data storage facilities and human resources that need to be equipped with data organization knowledge.

4.2. Analysis of experimental data from social media

The following are criteria or attributes from Twitter text data that are used in feature extraction, such as Source, "*shared_from*" as the attribute contains a data-sharing source, date, a text which contains a string in the form of an opinion or status, "*reactions*" which contains general reaction types such as '*likes', 'haha', 'love', 'wow', 'sigh', and 'grrr'*. Also used 273.348 "*comments"*, 42 "*post_id*", and 500 "*URL*". The attribute tests conducted with the 14 attributes above were tested using three main classes as a result of sentiment classification, namely positive, negative, and neutral classes. Where the basic classification of sentiments is based on training data. The training used manual labeling based on the results of human perception. There are 500 data tested in this study to test the analysis sentiment.

The classification results from the dataset built and has gone through several processes designed in the method section. The data has been through normal pre-processing for text data such as tokenization, stemming, stop-word elimination, and case folding. Furthermore, our text data is subject to a feature selection process using IG and MI, after post-tagging on word features. After our dataset is formed, the classification process with RNN. For RNN classification, the task is handled by the library of Python language. The sentiment classification about public complaints using RNN is carried in the interface. With this, it can be seen the results of the evaluation of public complaints against the Jambi City Government in visualization mode.

4.3. Analysis of sentiment classification specifications

The sentiment classification must easily contain information aspects of data. The sentiment classification was developed using Android programming (front end) and Python language programming (back end), during the testing we used an online server, and for documentation, we used unified modeling language UML design. The following Table 1 is the sentiment classification feature data of cases carried out in this study, and the views of the application of sentiment classification for Jambi City Government based on RNN and attribute selection can be seen in Figure 10.

Table 1 is the sentiment classification features description, whereas Figure 10 is an overview of sentiment classification for Jambi public complaint which showed the result of analyzing public sentiment. The data will be updated using new training data taken from tweets related to the query list about the sentiments of the people of Jambi City towards the government. Some of these features include the display of trending topics. Trending topic is taken from the weighting of feature selection, then also transformed into other infographics such as word cloud, or word cloud per period. The interface also receives complaints and public reports of Jambi City, this data will also combine with updated data on Twitter. The infographics are to be displayed as sentiment per period, sentiment per field and also displaying visualization and infographics for policyholders.

4.4. Results of experimental data with recurrent neural network

The following is a table of experimental results carried out from the data discussed in the previous section. From the text data obtained from Twitter, an experiment for sentiment classification with the addition of selection from word features. In the sentiment classification experiment, feature selection was carried out using 3 types of feature selection algorithms. Among others, the method of IG, MI, and without using any feature selection methods. Next, Table 2 shows the result of the sentiment classification experiment.

Table 1. Sentiment classification features

No	Features	Description of features
1	Showing trending topics	Displays problem topics raised on social media and cyberspace related to Jambi City
2	Displays word cloud	Displays the frequency of favorite words discussed on social media and cyberspace as well as public reports regarding Jambi City. The use case is based on text NLP visualized by the word cloud.
3	Displays word cloud obstacles	Displays the frequency of words in certain fields discussed in social media and cyberspace as well as public reports related to Jambi City. The use case is based on text processing NLP visualized by the word cloud.
4	Show word cloud per period	Displays the frequency of words in a certain period discussed on social media and cyberspace as well as public reports related to Jambi City. The use case is based on text processing NLP visualized by the word cloud.
5	Receiving complaints and public reports Jambi City	Receiving input complaints from all people in Jambi City, provided a selection of reporting categories. The input data of the test report is also used as data for text processing NLP which is visualized in sentiment, Wword cloud, and infographics.
6	Displays sentiment per period	Displays sentiment classification results from Digital data related to Jambi City in a certain period. Sentiment is displayed in chart form with positive, negative, and neutral classes. The use case is based on text processing NLP which is visualized by a sentiment graph.
7	Displays sentiment per field	Displays sentiment classification results from digital data related to Jambi City in certain fields. Sentiment is displayed in chart form with positive, negative, and neutral classes. The use case is based on text processing NLP which is visualized by a sentiment graph.
8	Displaying visualizations and infographics for policy holders (head of service)	Displays the visualization of data processing results of text and images. Data is a combined visualization of sentiment, word cloud, and trending topics.

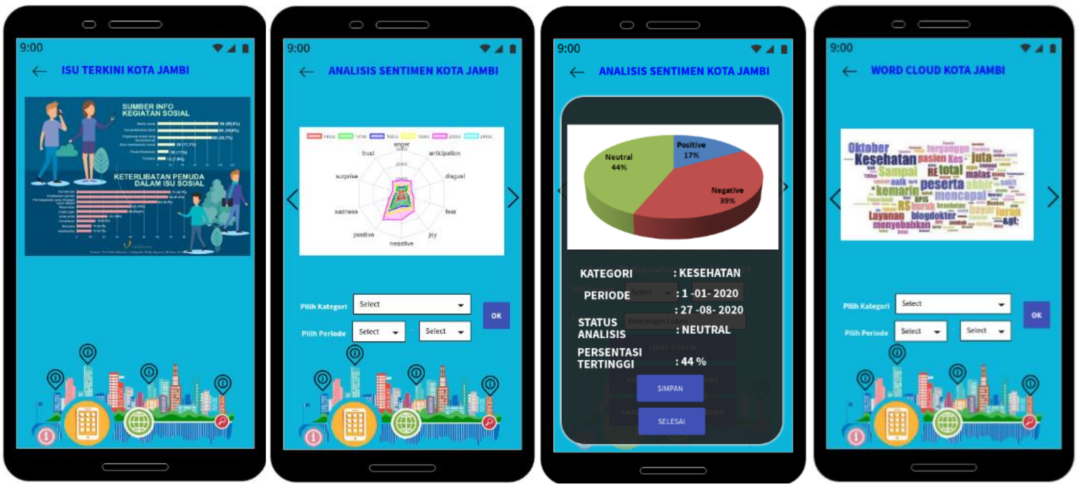


Figure 10. The views of the sentiment classification for Jambi City Government based on RNN and attribute selection

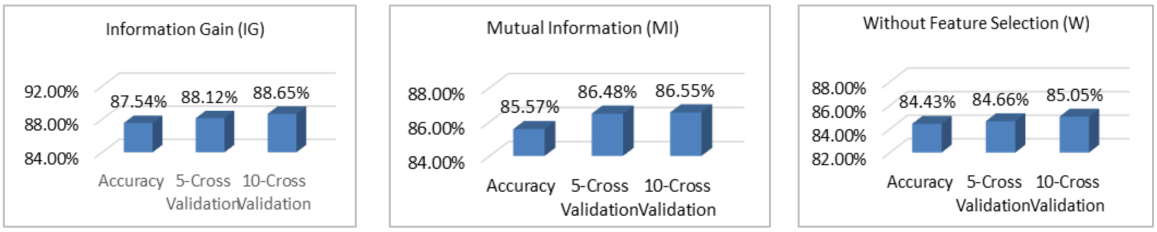
Table 2. The result of the sentiment classification experiment

Feature selection	Accuracy (%)	5 cross validation (%)	10 cross validation (%)
IG	87.54	88.12	88.65
MI	85.57	86.48	86.55
Without feature selection (W)	84.43	84.66	85.05

Table 2 shows the results of the comparison of classification sentiments for Jambi City community sentiments towards the government services using RNN. There are three experimental schemes in the sentiment classification section using the RNN algorithm, including classification by selecting word features from the dataset using the IG feature selection method, MI, and without using feature selection. The evaluation uses the accuracy and cross-validation values of 5 and 10. The following visualize the values from Table 2 regarding the results of the classification of the Jambi City community towards the Jambi City government services based on Twitter social media data using the feature selection in the RNN classification.

The following Figure 11 is the result chart of sentiment classification using some feature selection experiments.

From Figures 11(a) to (c), the results of the sentiment classification are shown with several classification models carried out, including a split test of 30% training data and 70% testing data, then with a 5-cross validation model and 10 cross validations. For the split testing data model, the data produces the highest value of 87.54% for testing with feature selection using IG. In the test model with 5 cross validation, the highest value is 88.12% still with feature selection with IG. In the testing model with 10 cross validations, the highest results were produced using attribute selection with an IG of 88.65%. For testing using MI, the results are in second place, and without using feature selection the classification results are the lowest value compared to after selecting the attribute. The result of the sentiment classification experiment can be seen in Table 3.



(a) (b) (c)

Figure 11. The result chart of sentiment classification; (a) IG, (b) MI, and (c) without feature selection for public complaint of Jambi City towards the government

Table 3. The result of the sentiment classification experiment

Evaluation parameter	Measurements	Results (%)
Recall sensitivity true positive rate (TPR)	TP/(FN+TP)	93.243
False positive rate (FPR) false alarm rate	FP/(TN+FP)	64.286
Specificity true negative rate (TNR)	TN/(TN+FP)	35.714
Precision	TP/(TP+FP)	92.000
False negative rate (FNR)	FN/(FN+TP)	6.757
Accuracy	(TP+TN)/(TP+TN+FP+FN)	86.800

Table 3 regarding the results of the confusion matrix measurement. The parameters were obtained from data calculations whose true negative (TN) is the amount of token data from the Twitter dataset with a negative class that is correctly detected, while false positive (FP) is negative data but detected as positive data. Meanwhile, true positive (TP) is positive data that is detected correctly, and of course, false negative (FN) is positive data that is detected incorrectly. With a recall value that shows the success rate of the system in sentiment classification for the Jambi City Government 93.243%. The precision of 92% shows that the accuracy of the method with the testing model that is carried out is sufficient to support the sentiment assessment of the Jambi City Government. From all the data tested, we distribute the overall class labeled by the system in its assessment of the Jambi City Government. The percentage of public sentiment class in Jambi City can be seen in Figure 12.

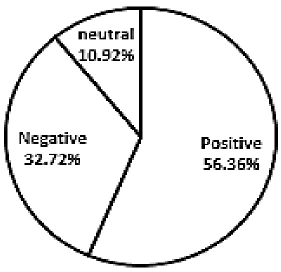


Figure 12. Results of the Jambi community complaints sentiment from Twitter data

Figure 12 is the percentage of extracted Twitter data with its attributes. Jambi people's complaint data from Twitter for positive sentiment still outperforms the negative class and is neutral. This means that the public's trust in the Jambi City Government is more than half of the complaint data on Twitter. From the test results, the use of feature selection is proven to improve classification performance. With the accuracy of all the test models carried out, the highest value was obtained at 88.65%, in the 10 cross validation model the highest results were produced using attribute selection with IG. The results of this sentiment classification can be used with high confidence. The range of values that contain errors can contain irrelevant word features or because the tweet uses the Jambi regional language, the performance has not reached the best value. The accuracy value obtained is still in the lowest range, namely 87.54%, and the highest is 88.65%, meaning that the sentiment classification analysis value still needs to be further developed to produce a better value.

5. CONCLUSION

From the tests carried out in this study on 500 sources of Twitter accounts, a test was carried out on the crawled term data to classify whether it belongs to the positive, negative, and neutral sentiment analysis class. For training data, tokens from feature selection are also tested using the IG and MI methods. From the tests carried out, the average use of feature selection can achieve a good value compared to no feature selection. Tests were carried out using a RNN with as many input layers as tokens or layers originating from the source, as many as 100 hidden layers, and 3 output layers. The output layer is a class resulting from the classification of text that has undergone sentiment classification. Sentiment classes are positive, negative, and neutral classes. From our research, Twitter data was analyzed using a RNN, with the accuracy of all the test models carried out, the highest value was obtained at 88.65%, in the 10 cross validation model the highest results were produced using attribute selection with IG. Then the results of this sentiment classification can be used with a fairly high level of confidence. The range of values that contain errors may contain relevant word features or because the tweet uses the Jambi regional language, the performance has not reached the best value. Recent observations indicate that this research shows that the use of feature selection can increase accuracy even if it is not significant. Future research may look into the other methods of weighting as the selection feature in sentiment analysis.

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