Elinvo (Electronics, Informatics, and Vocational Education)
Vol 10, No. 1, 2025, pp. 78-87

ISSN 2580-6424 (printed) | ISSN 2477-2399 (online)

Sentiment Analysis of Cooking Oil Prices in Indonesia Using the Long Short-Term Memory Method

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Article Info

Article history:
Received June 1, 2024
Revised February 13, 2025
Accepted April 29, 2025

Keywords:
Sentiment Analysis, Text Mining, Classification, LSTM

Abstract

The policy that was intensively discussed from early January to March 2022 was related to the setting and lifting of the Highest Retail Price for cooking oil, which was proven by the busy news on television, print media and social media. Many responses or speculations arise as a result of this policy. The importance of research on public speculation or sentiment analysis is to create a system model and find out how the public responds to government policy after the Highest Retail Price for cooking oil is determined and revoked, which ranges from February 4 to March 31 2022, as a benchmark and material. government considerations in making policy. The data that was collected in the period after the Maximum Retail Price (MRP) was set amounted to 904 datasets, and after the repeal of the MRP, it amounted to 874. Research can function as a basis for completing important information to support public policy decisions. The data is trained to obtain an optimal model and can predict sentiment with the Long Short-Term Memory (LSTM) model. To get the best model, random parameter testing was carried out using 80% of the training data and 20% of the validation dataset. The test results in fairly good accuracy with the softmax activation function, with an accuracy of 82.34%.

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INTRODUCTION

The population in Indonesia increases every year, including social media users. Social media has become a forum for analyzing responses or sentiments to evaluate products, news, topics and even public policies. Influence in the news can influence public opinion on a topic or government policy[1]. Social media, in addition to serving as a space for individuals and organizations to communicate with one another, also fulfils a democratic function for government institutions by enhancing transparency and public participation[2].

The policy that was widely discussed from early January to March 2022 was related to the establishment and revocation of the Maximum Retail Price (MRP) for cooking oil, as evidenced by the extensive coverage on television, print media, and social media. Many responses or speculations have arisen as a result of this policy. The increase in prices and the scarcity of cooking oil have resulted in panic buying among people in a number of cities. In microeconomics, if the market-clearing price is too high, the government can intervene in prices by imposing a price ceiling or maximum price, which is often called MRP.

This research on public speculation or sentiment analysis is to create a modelling system that can find out how the public responds to government policy after the MRP for cooking oil is established and revoked, which ranges from February 4 to March 31 2022, as a benchmark and one of the data samples for consideration in making policies. LSTM (Long Short-Term Memory) networks are particularly advantageous for sentiment analysis due to their ability to handle sequential data and capture long-term dependencies within text. Long short-term memory (LSTM) neural networks and attention mechanisms have been widely used in sentiment representation learning and the detection of texts [3]. To improve the predictive outcome of the LSTM model, the Adam optimizer is used to determine the learning rate [4]. Unlike traditional methods such as simple machine learning algorithms (e.g., SVM, Naive Bayes) or basic RNNs, LSTMs can maintain context across longer sequences of words, which is crucial in understanding sentiment, especially in complex or nuanced expressions like sarcasm or mixed emotions. They overcome the vanishing gradient problem, allowing the model to learn from longer passages of text without losing important information [5]. Additionally, LSTMs perform well on noisy, unstructured data commonly found in real-world sources like social media, making them highly effective for sentiment analysis tasks across diverse datasets and languages [6]. At the labelling stage, using the Indonesian Sentiment Lexicon, this method contains a set of words and expressions classified by sentiment polarity, which allows for more accurate analysis of opinions and emotions in Indonesian texts. This lexicon is very useful because it takes into account local linguistic features, slang, and cultural context, thus increasing the effectiveness of sentiment analysis for applications such as social media monitoring, customer feedback, and market research in Indonesia [7].

This research lies in the limited use of advanced sentiment analysis techniques like LSTM to study public sentiment about cooking oil price fluctuations, a crucial issue in Indonesia. While sentiment analysis is commonly applied to other areas, its use in analyzing commodity prices, especially essential goods like cooking oil, has been underexplored. The significance of this research is high, as understanding public sentiment can provide valuable insights for policymakers, businesses, and consumers, helping to predict reactions to price changes and inform decisions related to market regulation and consumer behavior [8].

METHODS

The establishment of the MRP is one of the government policies aimed at stabilizing food prices, reducing farmers' uncertainty, and ensuring that consumers have access to sufficient food at reasonable prices. The government's action in setting the MRP is a genuine act of governance (bestuurhandeling) and serves as an example of state intervention to realize the constitutional right to food sovereignty. Thus, the elements of the welfare state, particularly regarding the protection of the constitutional rights of every citizen, can be implemented effectively [9].

Sentiment Analysis

Sentiment analysis, commonly referred to as opinion mining, is a topic that is frequently used in the fields of data mining and natural language processing [10]. Sentiment analysis has a target that needs to be achieved, namely to separate, summarize and discover the information contained in a sentence using various techniques that are able to draw out the perspective and feelings intended by the person who wrote the sentence [11]. Sentiment can be interpreted as a positive or negative perspective on a person or group of people who are focused on something [12].

Sentiment analysis is generally divided into three levels, namely document level, sentence level and aspect level (fine-grained level) [13]. Document-level and sentence-level can be roughly divided into several levels. Sentiment analysis techniques can be divided into two types, namely learning-based and vocabulary-based. Learning base is a technique that uses training data and test data using a dictionary (opinion dictionary), lexically [14]. Aspect-based sentiment analysis is an advanced level of the research field of sentiment analysis [15].

Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a variation of Recurrent Neural Networks (RNN) designed to address the issue of long-term dependencies that can occur in traditional RNNs [16]. LSTM has the advantage of analyzing the relationship between time series data through its memory function [17]. Some variations of LSTM units do not have one or more gates or even produce other gates. For example, Gated Recurrent Units (GRUs) do not have output gates [18]. The model produced by LSTM is able to achieve competitive results compared to various models [19]. LSTM was adopted to capture long-term dependencies between words in a sentence [20]. LSTM can also be used for polarity-based sentiment analysis [21].

The purpose of the activation function is to determine the status of the neuron and whether its status will be activated or not. The value used as input for the sigmoid activation function is a real number, and the output value has a range between 0 and 1 [22]. The following is the calculation formula:

$$g(x) = 11 + e - x \quad \text{.......................................} \quad (1)$$

The value used as input for the Tanh activation function is a real number, and the output value has a range between -1 and 1. The following is the calculation formula:

$$g(x) = \frac{e^{x} - e^{-x}}{e^{-x} + e^{-x}} \quad \text{.......................................} \quad (2)$$

For the probability range value of the output of this softmax activation function, the value is 0 to 1, and the sum of all probabilities will be equal to one[23]. The following is the calculation formula:

$$g(x) = \frac{e^{xi}}{\sum_{j=1}^{n} e^{xj}} \quad \text{.......................................} \quad (3)$$

The Twitter Application Programming Interface (API) is a program/application that is already available on Twitter [24]. This facility can make it easier for developers to access what is stored on Twitter by scraping data, and allows developers to integrate several different applications' information simultaneously [25].

Indonesian Sentiment Lexicon

Indonesia Sentiment Lexicon can be an assistant in the automatic data labelling process. To determine this sentiment label, you need to calculate the weight score for positive words and the weight score for negative words in each sentence [7]. The weight score for sentences whose value is greater than zero is put into the positive class, and for sentences that get a weight score of zero, they are put into the neutral class, and for sentences whose value is less than zero, they are put into the negative class [26]. This research uses exploratory and supervised learning research methods. Supervised Learning consists of input and output, which can be converted into mathematical relationships so that predictions and classifications can be made based on research data [27]. Supervised Learning is a type of machine learning algorithm that uses a known data set (training data set) to make predictions [28].

The research framework in Figure 1 can be explained as follows :

Study of literature

Study and collect data about machine learning, sentiment analysis and related methods for research materials. The data collection technique used in this research involved searching for references from books, journals, and e-books related to the research problem and objectives.

Scraping Data from Twitter

The tweets data scraped from the Twitter social media server is data pulled from February to March 2022. This data collection was obtained using the Application Programming Interface (API) facility. In the process of extracting data from tweets, researchers used the keyword 'highest retail price of cooking oil'. The amount of data collected by the first scraping was 904 data points, and the amount of data collected by the second scraping was 874 data points.

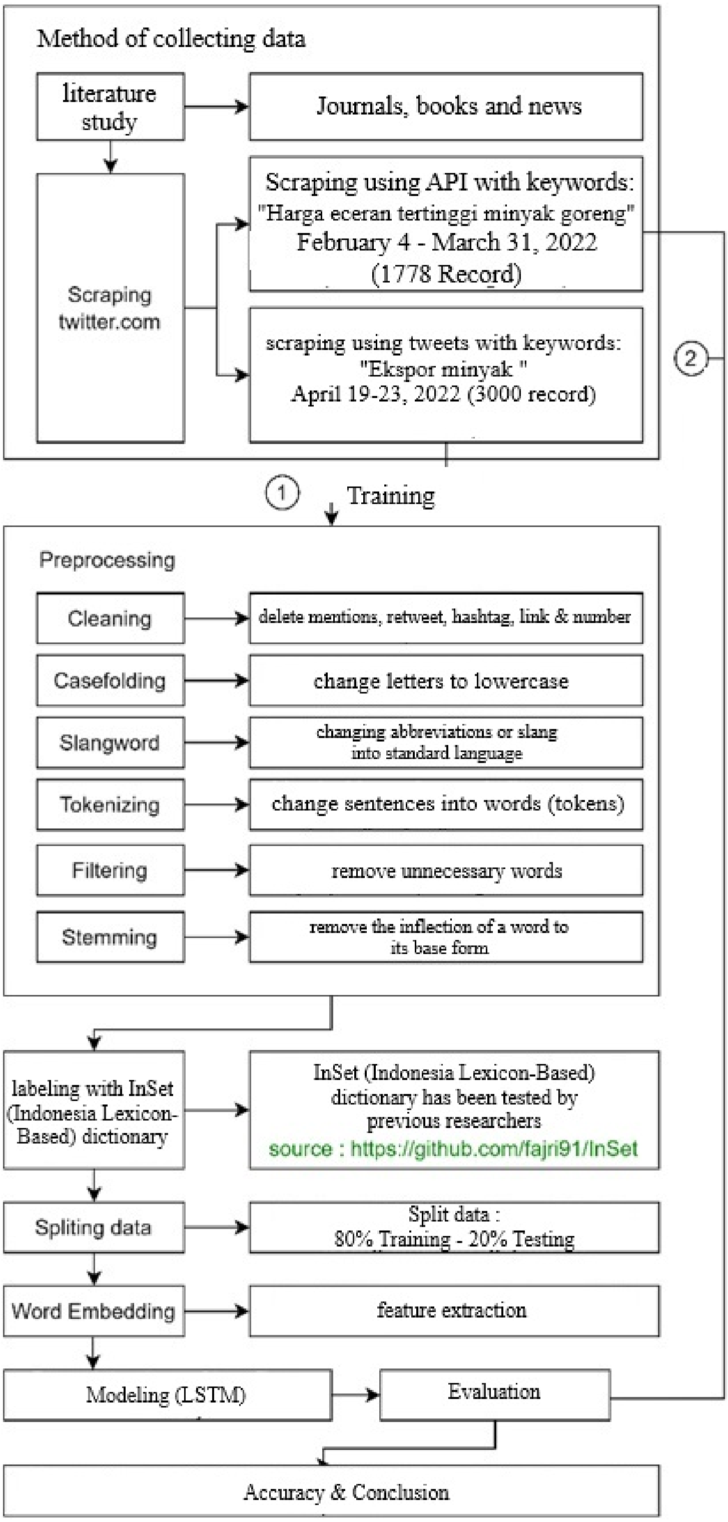


Figure 1. Framework

Table 1. Acquisition Data

Period	**Amount of data**
After the MRP is determined (4 February 2022 - 15 March 2022)	904 Data
After the MRP was revoked (16 March – 31 March 2022)	875 Data
Scraping via Twint with the keyword oil export (April 24, 2022)	3000 Data for modelling training materials

The data scraping results in Figure 2 are then entered into a dataframe using the Pandas library, so that the data in CSV format is easy to process[29]. The following is the data from scraping, which is in the form of a dataframe:

	id	username	date	tweet	n
0	1518001188532150272	Ashraflswanto	2022-04-23 22:57:41	Jokowi Larang Ekspor Minyak Goreng, Komisi VI ...	
1	1518000651611283456	MasAgustinus	2022-04-23 22:55:33	@geetracker @jokowi Uar negeriminyak gorenh na...	
2	1517998487291392000	lintang_ayoe	2022-04-23 22:46:57	@NayDonuts Usut aliran perijinannya itu mba, e...	
3	1517993363311828993	SitindaonZul	2022-04-23 22:26:35	Jangan cuma stop ekspor minyak sawit, kalau be...	
4	1517993308823310336	nurulhaqqy	2022-04-23 22:26:22	@kangnday @kompascom @Kemendag @KSPgoid @jokow...	
...	...	...	...	...	
2995	1516401531079172100	sagsongs	2022-04-19 13:01:13	@catchmeupid tolong suruh bapaknya gantiin min...	
2996	1516400823114543106	Awan_putih15	2022-04-19 12:58:24	Doi sbnrnya bukan korupsi minyak goreng atau n...	
2997	1516400723654717449	ingat_waspada	2022-04-19 12:58:00	Geger, Dirjen Kemendag Tersangka Kasus Ekspor ...	
2998	1516399835368210438	pikiran_rakyat	2022-04-19 12:54:28	Mendag Lutfi Buka Suara Setelah Pejabat Dirjen...	
2999	1516399661925351427	kumparan	2022-04-19 12:53:47	Dirjen Daglu Kemendag Indrasari Wisnu Wardhana...	

3000 rows × 7 columns

Figure 2. Data Load Results

RESULT AND DISCUSSION

Text Preprocessing

Functions used in the preprocessing stage include Cleaning Text, Case Folding, Convert Slangword, Tokenizing, Filtering/Stopword removal and Stemming [30]. Figure 3 shows the raw data from scraping that has not yet undergone preprocessing. Figure 4 above shows the data resulting from preprocessing.

Jokowi Larang Ekspor Minyak Goreng, Komisi VI ...
@geetracker @jokowi Uar negeriminyak gorenh na...
@NayDonuts Usut aliran perijinannya itu mba, e...
Jangan cuma stop ekspor minyak sawit, kalau be...
@kangnday @kompascom @Kemendag @KSPgoid @jokow...
...
@catchmeupid tolong suruh bapaknya gantiin min...
Doi sbnrnya bukan korupsi minyak goreng atau n...
Geger, Dirjen Kemendag Tersangka Kasus Ekspor ...
Mendag Lutfi Buka Suara Setelah Pejabat Dirjen...
Dirjen Daglu Kemendag Indrasari Wisnu Wardhana...

Figure 3. Before Text Preprocessing

[jokowi, larang, ekspor, minyak, goreng, komis...
[uar, negeriminyak, goreng, naikstop, ekspor, ...
[usut, alir, perijinannya, mbak, ekspor, nilai...
[setop, ekspor, minyak, sawit, benar, serius, ...
[untuk, usaha, minyak, goreng, ha, ha, ha, kas...
...
[nongol, sangka, mafia, minyak, goreng, enggak...
[tolong, suruh, bapak, ganti, minyak, yang, su...
[doi, sbnrnya, korupsi, minyak, goreng, ngambi...
[mendag, lutfi, buka, suara, jabat, dirjen, ke...
[dirjen, daglu, kemendag, indrasari, wisnu, wa...

Figure 4. Text Preprocessing Results

Text Mining

Labeling

Data that has gone through the preprocessing stage is then carried out an automatic labelling process using the Indonesian Sentiment Lexicon[koto] dictionary. This sentiment class is divided into three, namely positive sentiment, negative sentiment and neutral sentiment, which uses an automatic labelling function using the Indonesian Sentiment Lexicon dictionary.

text_clean	text_preprocessed	polarity_score	polarity
jokowi larang ekspor minyak goreng komisi vi d...	[jokowi, larang, ekspor, minyak, goreng, komis...	-3	negative
uar negeriminyak gorenh naikstop ekspor dalam ...	[uar, negeriminyak, gorenh, naikstop, ekspor, ...	-2	negative
usut aliran perijinannya itu mba eksport yang ...	[usut, alir, perijinannya, mbak, eksport, nila...	-3	negative
jangan cuma stop ekspor minyak sawit kalau ben...	[stop, ekspor, minyak, sawit, benar, serius, b...	-36	negative
tidak tepat utk pengusaha minyak goreng dong h...	[usaha, minyak, goreng, ha, ha, ha, kasihan, u...	2	positive
...	...	...	...
tiba tiba nongol tersangka kasus mafia minyak ...	[nongol, sangka, mafia, minyak, goreng, nimbun...	-1	negative
tolong suruh bapaknya gantiin minyak yg udah d...	[tolong, suruh, bapak, ganti, minyak, ekspor, ln]	-4	negative
doi sbnrnya bukan korupsi minyak goreng atau n...	[doi, sbnrnya, korupsi, minyak, goreng, ngambi...	-15	negative
mendag lutfi buka suara setelah pejabat dirjen...	[mendag, lutfi, buka, suara, jabat, dirjen, ke...	-5	negative
dirjen daglu kemendag indrasari wisnu wardhana...	[dirjen, daglu, kemendag, indrasari, wisnu, wa...	-3	negative

Figure 5. Labeling Results

Split Data

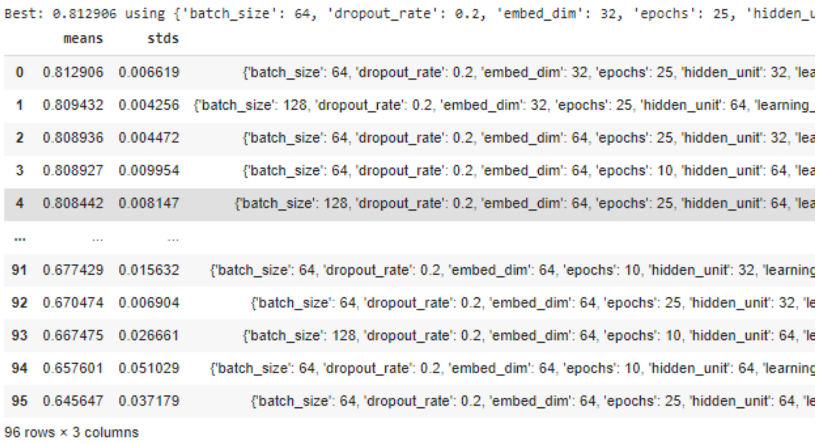
The initial preparatory step in creating a model is to make the previously processed (tokenized) text become untokenized with a sentence function, then tokenize the text with a certain maximum number of words to be stored based on word frequency, encode the target data into numeric values and then separate the data. Training data is used to train the dataset so that it can recognize data and produce a probability model, while test data is used to test sentiment classification [20]. In this research, the training data was 80% and the test data was 20%.

Modelling with LSTM

1) Create a Default Hyperparameter Model Function
   The default hyperparameters are set manually to assist in estimating the model parameters, which will serve as a reference in the search for the best model or hyperparameter tuning..
2) Looking for the Best Hyperparameter Model
   After determining the default hyperparameter model, next look for hyperparameter tuning. Its function is to find which model is the best to use so that the trained data can make good predictions, and the resulting accuracy is good. In setting hyperparameters or hyperparameter tuning, there are five strategies, including: Manual Search, Plot Search, Random Search, Bayesian Optimization and Evolutionary Algorithms [13]. researchers used one of 5 hyperparameter setting strategies, namely random search.

After obtaining the best model, with an accuracy of 0.821 in the 10th trial, the next step is to identify the model selected by the system for comparison with the random outcomes from the researcher and the system.

ISSN 2580-6424 (printed) | ISSN 2477-2399 (online)



Best: 0.812906 using {'batch_size': 64, 'dropout_rate': 0.2, 'embed_dim': 32, 'epochs': 25, 'hidden_u

	means	stds	
0	0.812906	0.006619	{'batch_size': 64, 'dropout_rate': 0.2, 'embed_dim': 32, 'epochs': 25, 'hidden_unit': 32, 'lea
1	0.809432	0.004256	{'batch_size': 128, 'dropout_rate': 0.2, 'embed_dim': 32, 'epochs': 25, 'hidden_unit': 64, 'learning_
2	0.808936	0.004472	{'batch_size': 64, 'dropout_rate': 0.2, 'embed_dim': 64, 'epochs': 25, 'hidden_unit': 32, 'lea
3	0.808927	0.009954	{'batch_size': 64, 'dropout_rate': 0.2, 'embed_dim': 64, 'epochs': 10, 'hidden_unit': 64, 'lea
4	0.808442	0.008147	{'batch_size': 128, 'dropout_rate': 0.2, 'embed_dim': 64, 'epochs': 25, 'hidden_unit': 64, 'lea
...	...	...	
91	0.677429	0.015632	{'batch_size': 64, 'dropout_rate': 0.2, 'embed_dim': 64, 'epochs': 10, 'hidden_unit': 32, 'learning
92	0.670474	0.006904	{'batch_size': 64, 'dropout_rate': 0.2, 'embed_dim': 64, 'epochs': 25, 'hidden_unit': 32, 'le
93	0.667475	0.026661	{'batch_size': 128, 'dropout_rate': 0.2, 'embed_dim': 64, 'epochs': 10, 'hidden_unit': 64, 'le
94	0.657601	0.051029	{'batch_size': 64, 'dropout_rate': 0.2, 'embed_dim': 64, 'epochs': 10, 'hidden_unit': 64, 'learning
95	0.645647	0.037179	{'batch_size': 64, 'dropout_rate': 0.2, 'embed_dim': 64, 'epochs': 25, 'hidden_unit': 64, 'le

96 rows × 3 columns

Figure 6. Hyperparameter Tuning Results

After obtaining the best value from the hyperparameter tuning results, the next step is to define the function in the command to evaluate the obtained accuracy.

Figure 7. Visualization of Hyperparameter Results

Based on testing parameters that were searched randomly, between 10 experiments by researchers and model searches with the system (hyperparameter tuning), the best model was obtained with the highest accuracy value of 0.823 using 'dropout_rate': 0.2, 'embed_dim': 32, 'hidden_unit': 32, 'learning_rate': 0.01, 'optimizers': Adam' 'optimizers': Adam', epochs: 25, batch_size: 64.

Evaluasi

After the model is formed, the model will then be evaluated using the Confusion Matrix. The Confusion Matrix aims to measure the performance of the model by calculating its accuracy value. At the evaluation process stage, 20% of the dataset will be used as test data. With the Confusion Matrix, the performance of a model that has several parameters can be seen. This Confusion Matrix technique is also known as the error matrix [10].

$$\text{Accuracy } = \frac{TP+TN}{\text{TP+TN+FP+FN}}\ x\ 100 \quad (4)$$

$$= \frac{272+65+78}{272+65+78+7+26+21+13+20+2} x100$$

$$= \frac{415}{504} x100$$

$$= 0.823412\ x\ 100$$

$$= 82{,}34\ \%$$

ISSN 2580-6424 (printed) | ISSN 2477-2399 (online)

From the accuracy results above, it can be seen that the accuracy value, which is a comparison of the classes predicted correctly by the classification model to the total existing data, is 82.34%.

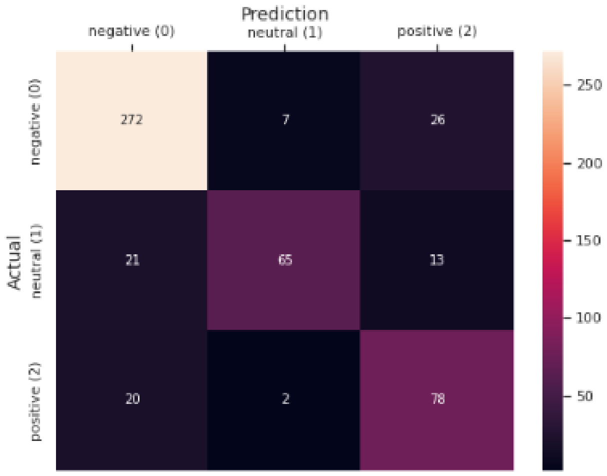


Figure 8. Confusion Matrix results

CONCLUSION

After modelling and testing, the resulting model is the result of the training dataset using the best hyperparameters, including softmax activation, 'dropout_rate': 0.2, 'embed_dim': 32, 'hidden_unit': 32, 'learning_rate': 0.01, 'optimizers': Adam', epochs: 25, batch_size: 64, is : (1) The results of analysis of public sentiment towards MRP for cooking oil two weeks after the enactment of Minister of Trade Regulation Number 6 of 2022 concerning Determination of MRP for Cooking Oil for the period 4 February 2022 to 15 March 2022 on Twitter using the Long Short Term Memory method show that out of 904 data tweets 52, 7% are negative, 42% are positive and 5.3% are neutral; (2) The results of the analysis of public sentiment towards the MRP for cooking oil after the MRP for cooking oil was revoked, namely March 16 2022 to March 31 2022 on Twitter using the Long Short Term Memory method, show that of the 874 tweet data, 58.8% were negative, 31.8% were positive, and 9.4% were neutral; (3) Accuracy or model testing with the Confusion Matrix produces accuracy data of 82.34%.

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