Sentiment analysis of customer response of telecommunication operator in Twitter using DCNN-SVM Algorithm

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Abstract. Along with the development of the times, social media is in great demand by various circles of society because social media allows users to express their thoughts or feelings freely. It is important for a company to know public responses about the product or service offered. With this public response, companies can analyze customer needs and plan more satisfying products or services. To be able to know the sentiments of responses, it is necessary to classify responses. Therefore, in this study used the Deep Convolutional Neural Network (DCNN) method as a feature extraction and Support Vector Machine (SVM) as its classification. The performance results of this research are 63% for accuracy, 63% for precision, and 50% for recall of test data.

1. Introduction

The era of big data and the internet of things penetrated in almost all fields, one of the most affected fields was the field of information and communication, therefore humans needed a telephone as a communication tool. According to Databoks, cell phone users in Indonesia reached 371.4 million users or 142% of the total population of 262 million [1]. That is, on average every Indonesian population uses 1-2 cell phones because one person sometimes uses 2-3 cell phone cards. Based on Press Release of Ministry of Communication of Indonesia, the number of provider customers in Indonesia was 254,792,159 customers. The increasing number of cellular phone users can be utilized by companies that provide telecommunications services to provide attractive offers to customers such as the internet, SMS and telephone packages.

Internet users in the world are increasing every year as well as in Indonesia. According to the results of the APJII survey (Association of Indonesian Internet Service Providers) in 2017, internet user penetration in Indonesia reached 143.26 million [2]. The number of internet users in Indonesia has increased by 7.96% compared to 2016 [2]. This figure shows the penetration of internet users by 54.68% of the total population of Indonesia [2]. One of the biggest Internet uses is for social media which is 87.13% of the total internet user penetration [2]. The most visited social media in Indonesia are YouTube 43%, Facebook 41%, followed by Instagram 38%, Twitter 27%, and Google Plus 25% [3]. The existence of social media has provided a platform for internet users to express and share their thoughts and opinions on different topics or events. Twitter is one of the social media used by companies, one of which is a telecommunications operator to monitor their reputation and brand by extracting and analyzing sentiments from tweets posted by the public about them, their markets, and competitors.

Sentiment analysis is a task to identify and classify sentiments and opinions expressed in a text to understand attitudes towards a particular product, topic, service and so on. The basic task in sentiment analysis is to group the polarity of the text in documents, sentences, or opinions. Polarity means...
whether the text in a document, sentence or opinion has a positive or negative aspect. In this study the data processing related to sentiment analysis via Twitter. Sentiment analysis of Twitter data and other similar micro-blogs faces several new challenges because of the short length of the irregular tweets of the content structure. Twitter with 280 characters makes users have to abbreviate a word and insert a slang. This shows that extraction is needed. This process is carried out using the Natural Language Processing method and the text analysis method [4]. A company needs to know the public response about the product or service they offer, with this public response, the company can analyze customer needs and make a more satisfying product or service plan. Besides that, it is undeniable that opinions that arise from the public can affect the image of a company [5]. However, monitoring and organizing public opinion on social media is also not easy. Opinions loaded are too many to process manually. Therefore, we need a special method or technique that can categorize responses on social media automatically, whether positive or negative.

2. Preliminaries

2.1. Sentiment Analysis
Sentiment analysis is a discipline that extracts people’s feelings, opinions, thoughts, and behavior from user text data using the Natural Language Processing (NLP) method [6]. Besides, sentiment analysis is also known as opinion mining. Sentiment analysis can be used to find opinion patterns about where people are happier or what people’s perceptions about a brand new product or service. Machine-based learning methods are divided into three, namely unsupervised learning, guided learning, and semi-supervised learning [7]. In the supervision of learning, there are several classification algorithms such as SVM, Naïve Bayes, and Neural Network.

2.2. Machine Learning
Machine learning is a discipline that studies and develops algorithms for learning and makes data predictions [6]. Machine learning focuses on predictions based on known data properties [6]. The purpose of machine learning is to generalize the patterns detected or make unknown rules from the examples given [8]. A problem that often occurs in machine learning is that large sets of training are needed for good generalizations, but large training courses are also more expensive computationally. Some of the most popular methods can be categorized as supervised learning and unsupervised learning [6]

2.3. Natural Language Processing
Natural Language Processing (NLP) is a discipline related to the study of methods and techniques for automatic analysis, understanding, and generation of natural languages, that is, languages that are written or spoken naturally by humans [6]. Natural Language Processing (NLP) is one of the techniques in Text Mining [9]. The challenges in Natural Language Processing often involve speech recognition being clear, requiring humans to be able to speak to computers in an appropriate, unambiguous and highly structured programming language.

2.4. Deep Learning
Deep learning is a subfield of machine learning that deals with algorithms that are inspired by the structure and function of the brain called artificial neural networks. Deep learning can be considered as a way to predict analysis automatically. Traditional machine learning algorithms are linear, whereas deep learning algorithms are stacked in a hierarchy that increases complexity and abstraction.

2.5. Word2Vec
Word2vec is a form of a method for presenting words into certain vector values developed by Google. The vector can help the machine learning algorithm to achieve better performance in NLP by grouping
words that are similar or similar. Word2vec itself is included in the neural network category that uses hidden layers and several non-linear layers in the algorithm.

One of the architectural models in Word2Vec for studying the representation of distributed words that tries to minimize computational complexity both of which use log-linear in the Skip-gram model. The Skip-gram Architecture Model predicts current words based on their context, it tries to maximize word classification based on other words in the same sentence. Can be used every word at this time to be able to predict words in a certain range before and after the present word.

The learning objective of the Skip-gram model is to find word representations that are useful for predicting surrounding words in sentences or documents. More formally, given the sequence of learning the words $w_1, w_2, ..., w_T$, the purpose of the Skip-gram model is to take advantage of the average opportunity [12].

$$\frac{1}{T} \sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j} | w_t)$$

where:
- $c$ = size of window
- $w$ = word
- $T$ = a lot of word learning
- $p(w_{t+j} | w_t)$ = conditional chance of the accuracy of the word $w_t$ against the word $w_{t+j}$

The basic skip-gram formula from $p(w_{t+j} | w_t)$ uses the softmax function:

$$p(w_{t+j} | w_t) = \frac{\exp(v_{w_{t+j}}^T v_{w_t})}{\sum_{w=1}^{n} \exp(v_{w}^T v_{w_t})}$$

where:
- $v_w$ = input vector representation of $w$
- $v_{w_{t+j}}$ = input vector representation of $w_{t+j}$
- $n$ = the number of words in the vocabulary

Figure 1. Skip-Gram
2.6. Deep Convolution Neural Network

Deep Convolutional Neural Network (DCNN) development of Convolutional Neural Network (CNN) while CNN itself, according to Wayan Suartika is the development of Multilayer Perceptron (MLP) which is designed to process two-dimensional data [10]. The difference between DCNN and CNN here is the number of layers [5]. So DCNN is a CNN with a higher number of layers [5]. In DCNN 12 layers are used while on CNN it is usually only 8 layers. CNN was first used in 1989 by Yann LeCun to classify zip code images [10]. CNN is generally used in two-dimensional classification, or images, but CNN can also be used in text.

Figure 2. DCNN architecture

2.6.1. Convolution Layer

Convolution is the first layer in the DCCN-SVM network architecture that extracts input data features. Convolution preserves the relationship between pixels by studying data features using small input data boxes. This is a mathematical operation that takes two inputs such as an image matrix and a filter or kernel.

In general, the results of the combination of word vectors from index \(i\) to \(i + j\) are as follows

\[
x_{i}, x_{i+1}, x_{i+2}, \ldots, x_{i+j}
\]  

where:

- \(x_i\) : word vectors that are in \(\mathbb{R}^{50}\)

To find a filter to produce a feature value, it can be formulated in equation 4.

\[
c_i = f(\text{net})
\]

where:

- \(c_i\) : feature map value at the \(i\)-index
- \(h\) : word window size
- \(w\) : filters that are in \(\mathbb{R}^{50}\)
- \(b\) : bias parameter

In this study, the non-linear function used is a Rectified Linear Unit (ReLU) function. The output of the function gives a positive output limit. The function can be written in equation 5.

\[
\text{ReLU}(x) = \max\{0, x\}
\]

So the equation becomes like this:

\[
c_i = \text{ReLU}(\text{net})
\]

with

\[
\text{net} = w \cdot x_{i:i+h-1} + b
\]

Filter \(w\) is applied to every possible word window in tweet sentences \(\{x_{1:h}, x_{2:h}, \ldots, x_{n-h+1:h}\}\) so that a feature map is produced in equation 8

\[
c = [c_1, c_2, \ldots, c_{n-h+1}]
\]
where \( c \) is a feature map.

### 2.6.2. Pooling Layer

The next layer is the pooling layer. The function of the pooling layer is as a non-linear down-sampling. The role of the pooling in the algorithm includes:

1. By eliminating suboptimal values, reduce the computation of the layer above it.
2. Provides a form of invariant translation

After obtaining a feature map derived from the convolution layer, each of the feature maps is carried out by the pooling operation on the pooling layer. At this layer important values are taken from the feature map by taking the maximum value in each feature map [7]. Mathematically, the pooling operation can be formulated as follows:

\[
\hat{c} = \max \{ c \} \tag{9}
\]

with

\( \hat{c} \): maximum value of feature map \( c \)

Because there are as many \( m \) filters, the result of the pooling layer is a vector consisting of the maximum value of each feature map and the number of \( m \) elements [9]. So it can be obtained:

\[
z = [\hat{c}_1, \hat{c}_2, \hat{c}_3, \ldots, \hat{c}_m] \tag{10}
\]

where \( z \) is a vector resulting from the pooling layer that will enter the next layer.

### 2.7. Support Vector Machine

Support Vector Machine (SVM) is naturally defined for the classification of binary numeric data. SVM is a method in classification that can analyze data or recognize patterns. SVM is a learning system that classifies using hypothesis space in the form of linear functions in a high dimensional feature space, trained with learning algorithms based on optimization theory by implementing learning bias derived from statistical learning theory [12]. SVM can be applied to numeric fields, including digit recognition handwriting, object recognition and speaker identification SVM processes text data into vectors.

In the concept of SVM trying to find the best separator (hyperplane) function among an infinite number of functions. The best separating hyperplane between the two classes can be found by measuring the hyperplane’s margin and finding its maximum point. The data in the boundary plane is called a support vector.

![Figure 3. SVM architecture](image)

To get the maximum point can be done by equation 11.

\[
\min \frac{1}{2} |w|^2 \tag{11}
\]
where:

\( w \) = the weighting parameter of SVM

To get the class value as follows:

\[
f(x) = W^T x + b
\]

(12)

where:

\( x \) : result vector from pooling layer
\( W \) : SVM parameter
\( b \) : bias parameter of SVM

For example, \( y \) is the label class of a tweet. If \( y \geq 0 \), then the value \( y = +1 \) and if \( y < 0 \), then the value \( y = -1 \). Based on this, it can be written as follows:

\[
f(x_i) \geq 0, \quad y = +1
\]

(13)

\[
f(x_i) < 0, \quad y = -1
\]

(14)

where:

\( f(x_i) \) : class value
\( y \) : tweet label

3. Testing and Analysis
3.1. Process Testing
Test the whole sentiment analysis process are data scrapping, data pre-processing and labeling.

3.1.1. Data Scrapping Results
The data scrapping process was taken from the accounts of 4 telecommunications operators in Indonesia which have been outlined in the limitation of the problems in chapter 1 namely OP1, OP2, OP3, and OP4. The scrapping process was carried out from 2-20 April 2019 and received 27,739 tweets. The following is a breakdown of the number of scrapping tweets for each telecommunications operator account in Table 1.

| Telecommunication Operator | Number of Tweet |
|----------------------------|-----------------|
| OP1                        | 10.868          |
| OP2                        | 7.783           |
| OP3                        | 2.141           |
| OP4                        | 6.947           |

3.1.1.1. Data Pre-processing Results
After pre-processing the data, there are currently 20,852 data. A lot of data has been duplicated and has been through the process of cleaning up tweets so that the data experienced a significant reduction of 6,887. The following is a breakdown of the number of tweets for each telecommunications operator account after going through the data pre-processing in Table 2.

| Telecommunication Operator | Number of Tweet |
|----------------------------|-----------------|
| OP1                        | 10.084          |
| OP2                        | 4.271           |
| OP3                        | 2.024           |
| OP4                        | 4.473           |

The following is a piece of data pre-processing results.
Table 3. Data Pre-processing Result Pieces

| Activity / Condition       | Result (in Indonesian)                                                                                                                                                                                                 |
|---------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Original Tweet            | OP4 masiiihh aja lemoootttt, Sampe kpn siih min? udah 2 jam lohh @myOP4Care ☝️                                                                                                                                       |
| Delete URLs               | OP4 masiiihh aja lemooootttt, Sampe kpn siih min? udah 2 jam lohh ☝️                                                                                                                                                  |
| Delete punctuation, number | OP4 masiiihh aja lemooooottt sampe kpn siih min udah jam lohh                                                                                                                                                         |
| and symbols               |                                                                                                                                                                                                                       |
| Delete repeated words     | OP4 masiihh aja lemoott Sampe kpn siih min udah jam lohh                                                                                                                                                               |
| Lowercase                 | OP4 masiihh aja lemoott sampe kpn siih min udah jam lohh                                                                                                                                                               |
| Tokenizing                | ['OP4', 'masiihh', 'aja', 'lemoott', 'sampe', 'kpn', 'siih', 'min', 'udah', 'jam', 'lohh']                                                                                                                                 |
| Correct words             | ['OP4', 'masiih', 'saja', 'lemot', 'sampai', 'kapan', 'siih', 'min', 'sudah', 'jam', 'lohh']                                                                                                                                 |
| Delete stopwords          | ['OP4', 'masih', 'lemot', 'sampai', 'kapan', 'sudah', 'jam',]                                                                                                                                                         |

The data labeling process is carried out by 3 different people than to get the final label that will be used for the next process is obtained from 2 or more labels selected by each annotator. Here are the final results of label distribution obtained from the labeling process of 3 different people.

Table 4. Amount of Data Distribution Based on Label

| Label | Number of Tweet |
|-------|-----------------|
| Negative | 20.017         |
| Positive | 835           |

Here are the final results of data distribution based on topics obtained from the labeling process of 3 different people.

Table 5. Number of Tweets Distribution by Topic

| Topic | Label | Number of Tweet |
|-------|-------|-----------------|
| OP1   | Negative | 9.841           |
| OP2   | Negative | 3.995           |
| OP3   | Negative | 1.826           |
| OP4   | Negative | 4.355           |
| OP1   | Positive  | 243             |
| OP2   | Positive  | 276             |
| OP3   | Positive  | 198             |
| OP4   | Positive  | 118             |

Based on Table 5, the data are not balanced either in topic or labeling because in the topic the number of OP1 tweets is more and the number of OP3 tweets is less. This is caused by the limitations of the data collection process. The number of customers complaining at OP1 is also higher than OP2, OP3, and OP4.

Data of each telecommunications operator will be divided into five combinations, namely 30% positive data and 70% negative data, 40% positive data and 60% negative data, 50% positive data and 50% negative data, 60% positive data and 40% negative data and 70% positive data and 30% negative data.

The following is a summary of the results of several cases of positive and negative data sharing.
Table 6. Result of 30% Positive Data and 70% Negative Data Accuracy Results

|       | Positive 30% | Negative 70% | DCNN Accuracy | DCNN-SVM Accuracy |
|-------|--------------|--------------|---------------|-------------------|
| Total | 300          | 700          |               |                   |
| OP2   | 241          | 559          | 64%           | 70%               |
|       | 59           | 141          | 71%           | 70%               |
|       | 276          | 644          |               |                   |
| OP1   | 216          | 520          | 59.24%        | 71%               |
|       | 60           | 124          | 63.59%        | 67%               |
|       | 180          | 420          |               |                   |
| OP3   | 140          | 340          | 60.42%        | 71%               |
|       | 40           | 80           | 55%           | 67%               |
|       | 135          | 315          |               |                   |
| OP4   | 103          | 257          | 41%           | 71%               |
|       | 32           | 58           | 40%           | 64%               |

Based on Table 6, it can be seen that the highest accuracy of training data and DCNN test data is OP2 with a value of 64% and 71%. While the highest DCNN-SVM training data accuracy results are OP4, OP1, and OP3 with a score of 71% and the highest DCNN-SVM test data result is OP2 with a value of 70%.

Table 7. Results of 40% Positive Data and 60% Negative Data Accuracy

|       | Positive 40% | Negative 60% | DCNN Accuracy | DCNN-SVM Accuracy |
|-------|--------------|--------------|---------------|-------------------|
| Total | 300          | 450          |               |                   |
| OP2   | 246          | 354          | 59.17%        | 59%               |
|       | 54           | 96           | 63.33%        | 63%               |
|       | 276          | 414          |               |                   |
| OP1   | 222          | 330          | 56.88%        | 60%               |
|       | 54           | 84           | 47.10%        | 62%               |
|       | 180          | 270          |               |                   |
| OP3   | 144          | 216          | 50.83%        | 60%               |
|       | 36           | 54           | 37.78%        | 61%               |
|       | 134          | 201          |               |                   |
| OP4   | 105          | 163          | 52.99%        | 60%               |
|       | 29           | 38           | 46.27%        | 57%               |

Based on Table 7, it can be seen that the highest accuracy of training data and DCNN test data is OP2 with a value of 59.17% and 63.33%. While the highest DCNN-SVM training data accuracy results are OP4, OP1 and OP3 with a value of 60% and the highest DCNN-SVM test data results are OP2 with a value of 63%.
Table 8. Results of 50% Positive Data and 50% Negative Data Accuracy

|        | Positive 50% | Negative 50% | DCNN Accuracy | DCNN-SVM Accuracy |
|--------|--------------|--------------|----------------|-------------------|
| **Total** | 300          | 300          |                |                   |
| **OP2** Training Data | 240          | 240          | 73%            | 59%               |
| Testing Data       | 60           | 60           | 67%            | 54%               |
| **Total**          | 276          | 276          |                |                   |
| **OP1** Training Data | 220          | 221          | 51.5%          | 58%               |
| Testing Data       | 56           | 55           | 54%            | 53%               |
| **Total**          | 180          | 180          |                |                   |
| **OP3** Training Data | 146          | 142          | 55.9%          | 61%               |
| Testing Data       | 34           | 38           | 54%            | 56%               |
| **Total**          | 135          | 135          |                |                   |
| **OP4** Training Data | 110          | 106          | 50.46%         | 58%               |
| Testing Data       | 25           | 29           | 52.78%         | 54%               |

Based on Table 8, it can be seen that the highest accuracy of DCNN training data is OP3 with a value of 58.68% and the highest DCNN test data is OP4 with a value of 53.70%. While the highest accuracy of DCNN-SVM training data is OP3 with 57% value and the highest DCNN-SVM test data result is OP1 with 61% value.

Table 9. Results of 60% Positive Data and 40% Negative Data Accuracy

|        | Positive 60% | Negative 40% | DCNN Accuracy | DCNN-SVM Accuracy |
|--------|--------------|--------------|----------------|-------------------|
| **Total** | 300          | 200          |                |                   |
| **OP2** Training Data | 241          | 159          | 43%            | 61%               |
| Testing Data       | 59           | 41           | 40%            | 58%               |
| **Total**          | 276          | 184          |                |                   |
| **OP1** Training Data | 225          | 143          | 54.35%         | 62%               |
| Testing Data       | 51           | 41           | 45.65%         | 55%               |
| **Total**          | 180          | 120          |                |                   |
| **OP3** Training Data | 142          | 98           | 60.42%         | 68%               |
| Testing Data       | 38           | 22           | 55%            | 70%               |
| **Total**          | 135          | 90           |                |                   |
| **OP4** Training Data | 101          | 79           | 62.22%         | 56%               |
| Testing Data       | 34           | 11           | 62.22%         | 76%               |

Based on Table 9, it can be seen that the highest accuracy of training data and DCNN test data is OP2 with a value of 59.17% and 63.33%. While the highest DCNN-SVM training data accuracy results are OP4, OP1 and OP3 with a value of 60% and the highest DCNN-SVM test data results are OP2 with a value of 63%.
Table 10. Results of 70% Positive Data and 30% Negative Data Accuracy

|        | Positive 70% | Negative 30% | DCNN Accuracy | DCNN-SVM Accuracy |
|--------|--------------|--------------|---------------|-------------------|
| Total  | 294          | 126          |               |                   |
| OP2    | 235          | 101          | 70.54%        | 70%               |
| Testing Data | 59    | 25           | 70.24%        | 70%               |
| Total  | 273          | 117          |               |                   |
| OP1    | 216          | 96           | 53.85%        | 70%               |
| Testing Data | 57    | 21           | 50%           | 71%               |
| Total  | 175          | 75           |               |                   |
| OP3    | 138          | 62           | 52.5%         | 69%               |
| Testing Data | 37    | 13           | 56%           | 74%               |
| Total  | 133          | 57           |               |                   |
| OP4    | 102          | 50           | 63.16%        | 68%               |
| Testing Data | 31    | 7            | 57.89%        | 79%               |

Based on Table 10, it can be seen that the highest accuracy of training data and DCNN test data is OP2 with a value of 70.54% and 70.24%. While the highest DCNN-SVM training data accuracy results are OP2 and OP1 with 70% value and the highest DCNN-SVM test data result is OP4 with a value of 79%.

The following is the average accuracy of all combinations for all telecommunications operators in Table 11.

Table 11. The average of Accuracy of All Combinations of All Operators

|        | Accuracy 30%-70% | 40%-60% | 50%-50% | 60%-40% | 70%-30% | Average |
|--------|-----------------|---------|---------|---------|---------|---------|
| OP2    | Training Data   | 70%     | 59%     | 59%     | 61%     | 70%     | 64%     |
|        | Testing Data    | 70%     | 63%     | 54%     | 58%     | 70%     | 63%     |
| OP1    | Training Data   | 71%     | 60%     | 58%     | 62%     | 70%     | 64%     |
|        | Testing Data    | 67%     | 62%     | 53%     | 55%     | 71%     | 62%     |
| OP3    | Training Data   | 71%     | 60%     | 61%     | 68%     | 69%     | 66%     |
|        | Testing Data    | 67%     | 61%     | 56%     | 70%     | 74%     | 66%     |
| OP4    | Training Data   | 71%     | 60%     | 56%     | 58%     | 68%     | 63%     |
|        | Testing Data    | 64%     | 57%     | 56%     | 54%     | 79%     | 62%     |
| Average Training Data |       |         |         |         |         | 64%     |
| Average Testing Data    |       |         |         |         |         | 63%     |

Based on Table 11, it can be shown that the highest average accuracy of training data is OP3 and the highest average accuracy of test data is OP3.

Table 12. Average Recall of All Combinations of All Operators

|        | Recall 30%-70% | 40%-60% | 50%-50% | 60%-40% | 70%-30% | Rata-rata |
|--------|----------------|---------|---------|---------|---------|-----------|
| OP2    | Training Data  | 70%     | 59%     | 59%     | 60%     | 70%       | 64%       |
|        | Testing Data   | 70%     | 64%     | 54%     | 59%     | 70%       | 63%       |
| OP1    | Training Data  | 71%     | 60%     | 58%     | 53%     | 69%       | 62%       |
|        | Testing Data   | 67%     | 61%     | 53%     | 45%     | 73%       | 60%       |
| OP3    | Training Data  | 71%     | 60%     | 61%     | 60%     | 69%       | 64%       |
|        | Testing Data   | 67%     | 60%     | 56%     | 65%     | 74%       | 64%       |
| OP4    | Training Data  | 50%     | 61%     | 58%     | 56%     | 67%       | 58%       |
|        | Testing Data   | 50%     | 57%     | 54%     | 76%     | 82%       | 64%       |
| Average Training Data |       |         |         |         |         | 62%       |
| Average Testing Data    |       |         |         |         |         | 63%       |
Based on **Table 12**, it can be shown that the highest average training data recall is OP2 and OP3 and the highest average test data recall is OP3 and OP4.

**Table 13. Average Precision of All Combinations of All Operators**

|            | Precision          |
|------------|--------------------|
|            | 30%:70% | 40%:60% | 50%:50% | 60%:40% | 70%:30% | Rata-rata |
| OP2        | Training Data     | 49%     | 35%     | 59%     | 36%     | 49%       | 46%       |
| OP2        | Testing Data      | 50%     | 41%     | 54%     | 35%     | 49%       | 46%       |
| OP1        | Training Data     | 50%     | 36%     | 58%     | 52%     | 48%       | 49%       |
| OP1        | Testing Data      | 45%     | 37%     | 53%     | 42%     | 53%       | 46%       |
| OP3        | Training Data     | 50%     | 36%     | 62%     | 76%     | 48%       | 54%       |
| OP3        | Testing Data      | 44%     | 36%     | 56%     | 77%     | 55%       | 54%       |
| OP4        | Training Data     | 51%     | 37%     | 61%     | 31%     | 45%       | 45%       |
| OP4        | Testing Data      | 42%     | 32%     | 59%     | 76%     | 67%       | 55%       |

| Average Training Data | 48% |
| Average Testing Data  | 50% |

Based on **Table 13** it can be shown that the highest average training data precision is OP3 and the highest average test data precision is OP4.

The following is an average of each training data performance and test data in **Table 14**.

**Table 14. Average Overall Performance**

|               | Accuracy | Precision | Recall |
|---------------|----------|-----------|--------|
| Average Training Data | 64%     | 62%       | 48%    |
| Average Testing Data   | 63%     | 63%       | 50%    |

Based on **Table 14**, it can be shown that the average accuracy of training data is 64%, the average precision of training data is 62% and the average recall of training data is 48%. The average accuracy of test data is 63%, the average precision of test data is 63% and the average recall of test data is 50%.

**4. Conclusion**

Based on the results of the trials conducted, it can be concluded that:

a. How to do sentiment analysis of telecommunications operator customer responses on Twitter through data scraping, data pre-processing, data labeling, word2vec, and the formation of classification models using the DCNN-SVM algorithm.

b. The labeling results obtained 20,017 negative datasets and 835 positive datasets. The words that often appear in the OP2 dataset are ‘no’, ‘OP2’, and ‘package’. The OP1 dataset is ‘no’, ‘pulse’ and ‘OP1’. In the OP3 dataset is ‘no’, ‘signal’, and ‘OP3’. The OP4 dataset is ‘no’, ‘OP4’, and ‘signal’.

c. The performance results of this study are test data accuracy of 63%, test data precision by 63% and recall test data by 50%.

d. The most complaining telecommunications operator customers are OP1.

**5. References**

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