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Analyzing the Impact of Body Shaming on Twitter: A Study Using Naive Bayes Classifier and Machine Learning

Karno Diantoro[1], Rinaldo[2], Anwar T. Sitorus[3], Abdur Rohman[4]
Mercusuar College of Management and Informatics (STMIK Mercusuar)
Correspondent : karno@mercusuar.ac.id [1]

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ABSTRACT: Twitter is one type of social media that is still widely used today. However, it happens frequently for Twitter users to post remarks that tend to criticize other Twitter users. Twitter users routinely make nasty remarks regarding body shaming, which has detrimental impacts on the victims such as diminishing self-esteem, leading to depressive illnesses, and, more seriously, raising the chance of suicide. Body shaming is the practice of criticizing someone's physical attributes, such as being slim, overweight, or having a flat nose. This study will use the Naive Bayes Classifier approach to do sentiment analysis based on the actions of body shaming on Twitter. Based on the performance testing results of Accuracy, Precision, and Recall using Machine Learning Rapid Miner with an initial dataset of 1000 body shaming tweets and a test dataset of 329 tweets, the following results were obtained: Accuracy of 80.55%, positive Precision of 100%, negative Precision of 80.43%, positive Recall of 3.03%, and negative Recall of 100%. In the preprocessing stage, tokenization resulted in a word cloud with the top 5 words being "overweight" at 51%, "body shaming" at 20%, "thin" at 11%, "people" at 10%, and "eating" at 8%.

Keywords: Twitter, Naïve Bayes Classifier, Machine Learning Rapid Miner, Body shaming

INTRODUCTION

Information is now readily available because to recent technology developments, and people now express their thoughts in a variety of ways. Social media has had a big impact on daily relationships, language, culture, and lifestyle. Dorsey established Twitter, which is still widely used today. However, a lot of Twitter users publish unfavorable remarks, information, or viewpoints that could offend others, such body shaming.

Body shaming can be extremely damaging, leading to despair, low self-esteem, and an increased risk of suicide. By identifying whether tweets are favorable or negative, sentiment analysis can be used to examine Twitter user behavior. A confusion matrix can be used to assess the accuracy, precision, and recall of the Naive Bayes Classifier technique.

METHOD

A classification approach built on the foundation of Bayes' theorem is the Naive Bayes Classifier. The Bayes' theorem, a classification technique that makes use of probability and statistics and predicts future probabilities based on historical data, was developed by the English scientist Thomas Bayes. The Nave Bayes Classifier's fundamental characteristic is its strong (nave) assumption of the independence of each condition or occurrence.

(Olson & Delen, 2008) asserts that Nave Bayes determines the likelihood that a decision class is accurate in light of the information object vector for each decision class. This algorithm takes for granted the independence of object characteristics. The "master" decision table's frequencies are used to determine the probabilities that go into creating the final estimate.

When compared to other classifier models, the Naive Bayes Classifier performs excellently. Naive Bayes Classifier has a greater accuracy rate compared to other classifier models, according to Xhemali and Hinde Stone in their study "Naive Bayes vs. Decision Trees vs. Neural Networks in the Classification of Training Web Pages." When compared to other classifier models, the Naive Bayes Classifier performs excellently. Naive Bayes Classifier has a greater accuracy rate compared to other classifier models, according to Xhemali and Hinde Stone in their study "Naive Bayes vs. Decision Trees vs. Neural Networks in the Classification of Training Web Pages."

This method has the benefit of requiring little training data, which makes it easier to estimate the parameters needed for classification. Because it presumes that variables are independent, classification requires simply the variance of a variable inside a class rather than the whole covariance matrix.

By adding the frequencies and combinations of values from the input dataset, the Naive Bayes classification method creates a set of probabilities. The approach relies on the Bayes theorem and assumes that, depending on the values of the class variable, all attributes are either independent or not interdependent. The foundation of Naive Bayes is the simplification that, given the output value, attribute values are conditionally independent. In other words, the likelihood of observing them together, given the output value, is the sum of the individual probabilities. Utilizing Naive Bayes has the benefit of requiring little to no training data to estimate the parameters needed for the classification process. Naive Bayes frequently outperforms expectations in a wide variety of real-world scenarios.

The following gives the Bayes' theorem's equation:

$$P(H|X) = \frac{P(X|H).P(H)}{P(H)} \qquad (2.1)$$

X : data with an unclassified class

H : Speculate about data utilizing a certain class

P(H|X): Based on X, what is the likelihood that hypothesis H will occur? (posterior probability)

P(H) : occurrence of hypothesis H (prior probability)

P(X|H): Hypothesis H's condition and probability of X

P(X) : probability of H.

Understanding that the classification process needs a set of cues to identify the proper class for the sample being studied is crucial to understanding the Naive Bayes approach. Therefore, the following modifications are made to the Naive Bayes approach:

$$P(C|F1 \dots . Fn) = \frac{P(C)P(F1 \dots Fn|C)}{P(F1 \dots Fn)} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2.2)$$

Where C stands for the class and F1 through Fn for the distinguishing cues that must be present in order to classify something. As a result, the formula explains that the likelihood of a specific set of characteristic samples entering class C (Posterior) is the likelihood of class C occurring before the entry of that sample, which is frequently referred to as prior, multiplied by the likelihood of the characteristics in the sample occurring in class C, which is divided by the likelihood of the characteristics occurring globally (also called evidence). Thus, the following sentence can also be used to express the aforementioned formula:

$$posterior = \frac{prior\ x\ likelihood}{evidence} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2.3)$$

For every class in a sample, the Evidence value stays the same. Against establish which class a sample will be categorized into, the posterior value will later be compared to the posterior values of other classes.

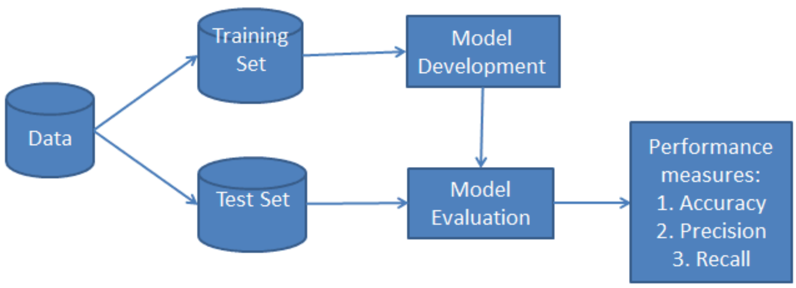

Figure 1 Naïve Bayes Classification

Applied Nave Bayes

1. classifying text documents, such as academic texts or news pieces.
2. as a probabilistic machine learning technique.
3. in support of automated medical diagnosis.
4. identifying or removing spam.

Benefits of Naive Bayes

1. both quantitative and qualitative data may be employed.
2. need a small bit of info.
3. doesn't require a lot of training data.
4. Calculations can overlook missing values.
5. swift and effective computations.
6. Simple to comprehend.
7. Simple to use.

8. It is possible to tailor document classification to a person's needs.
9. The code is straightforward when applied to programming.
10. both binary and multiclass categorization is possible .

Naive Bayes disadvantages

1. The prediction probability will be 0 if the conditional probabilities are also zero.
2. Given that there is frequently some correlation between variables, the assumption of their independence can lead to reduced accuracy.
3. A single probability cannot be used to gauge its correctness. To validate its accuracy, more proof is required.
4. Making decisions requires knowledge of the situation at hand or of previous events. This prior knowledge is vital to its success. There are numerous holes that could lessen its efficacy.
5. Only able to identify words; not capable of working with visuals.

RESULT AND DISCUSSION

Research Flow

There are multiple stages to the process that was used in this research. The approach starts with gathering twitter data and continues with preprocessing, first data processing, the Naïve Bayes classifier algorithm, and performance analysis. The graphic displays the study procedure flowchart in diagrammatic form.

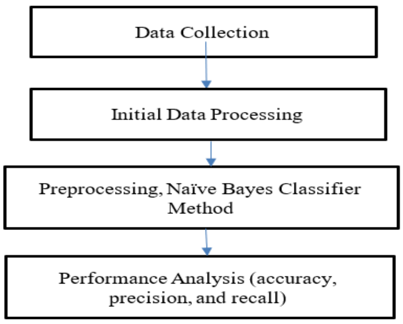

Figure 2 Research Flow

A. Phase of Data Collection:

This study's phases involve gathering tweets from Twitter that include body-shaming terms like "slim," "bald," "chubby," "snub-nosed," and so on. The information obtained does not include pictures and is restricted to statements in the Indonesian language that contain body-shaming terminology.

The Twitter program is used in the tweet data collection process. Data about tweets is retrieved from the Twitter server via Twitter. There are a thousand pieces of data in all. Preprocessing, which includes cleaning and tokenization, is the following step. The next step is called cross-validation (in this stage, the dataset is divided into two parts: training data and testing data, with 80 percent for training data and 20 percent for testing data).

The Naïve Bayes Classifier technique implementation is the following step (in this stage, weighting is done using the method through the Rapid Miner software). The performance study of the Naïve Bayes Classifier technique comes next (accuracy, precision, and recall). Making decisions based on the outcomes of the performance stage computations is the last step. The following figure shows the steps involved in the data collection stage:"

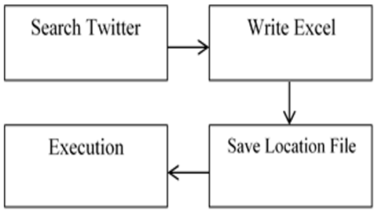

Figure 3 Data Collection Process

B. First-Hand Data Handling

The Naïve Bayes Classifier approach is employed to classify the gathered data after RapidMiner is utilized for sentiment analysis in this study. The initial data that was imported into Excel from Twitter is shown below:

Table 1 Initial Data

Created-At	From-User-Id	To-User	To-User-Id	Language	Source	Text
2023-07-02 23:42:55	117199215091	tantaeby	1551018600	in	<a href=	@tantaeby Kalau dia gendut jadi tambah mbull dan gemas lihatnya
2023-07-02 23:42:46	157033424687	desioctari	1641326231	in	<a href=	@desioctarina Gendut juga masih cuantik
2023-07-02 23:42:05	159565556976	cuanbossl	1397383856	in	<a href=	@cuanbossku Kd kna gendut
2023-07-02 23:39:36	1505861674636435462		-1	in	<a href=	duh banh nyemil roti jam segini ap bkin gendut
2023-07-02 23:37:42	154777722099	SATOURU	1469941612	in	<a href=	@SATOURU Muka Babu, Bopung, Jelek Menor, Gendut gentong air Tocil, Kurcaci, Paud
2023-07-02 23:35:58	153091431825	kochengfs	243647729	in	<a href=	@kochengfs Kamu gendut mara mara mulu, nanti tambah bengkak
2023-07-02 23:32:49	154777722099	SATOURU	1469941612	in	<a href=	@SATOURU muka Babu, Pendek, Bocah Kampung Menor, Jelek, Gendut, Bulet Kasihan gak punya pasangan
2023-07-02 23:32:07	1185007879243194368		-1	in	<a href=	Gendut badmud https://t.co/68gnDFxiSO
2023-07-02 23:29:55	1223984750508953600		-1	in	<a href=	Knp smua orng blngg i kurus i msh gendut
2023-07-02 23:29:21	1338731941		-1	in	<a href=	merasa gak pantes aja buat siapa^2 udah gendut, pendek, item, miskin, banyak utang.
2023-07-02 23:27:00	237216897		-1	in	<a href=	Kek gada angin gada hujan whatsapp begini. Maksudnya baik kali ya menurut dia ada baiknya memasang dp yang anglenya bikin orang y
2023-07-02 23:25:25	1180263526339792896		-1	in	<a href=	RT @lalalosthi: Masih insecure gada yg mau nikahin krena aku
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	@notyourtatjana Jablay Bookingan open BO Muka Babu, Jelek, Bocah Kapung Gendut, Bantet, Bulet, Pendek

The process, comprising several analysis stages, is as follows:

1. Data Collection Process (Crawling)

RapidMiner is the data processing technology used in this research's sentiment analysis data collecting and Twitter data crawling processes.

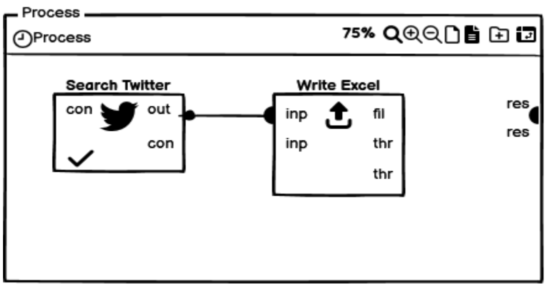

Figure 4 Data Collecting And Twitter Data Crawling Processes

2. Preprocessing Data

Data preprocessing, which includes all forms of processing done on unprocessed data to get it ready for more data processing like data visualization and model building, is a part of data preparation.

At this point, the data entered is unprocessed. The cleaning and tokenizing procedures are two of the data preprocessing procedures used in this investigation.

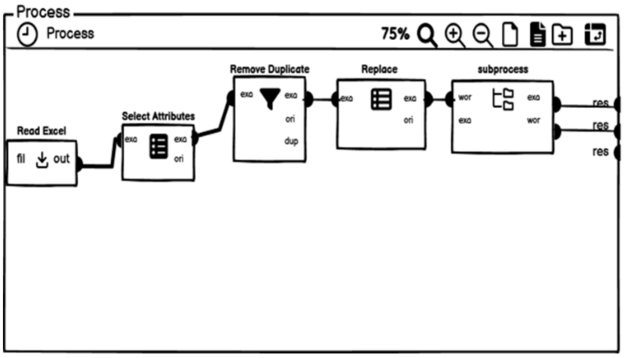

Figure 5 Processes Cleaning

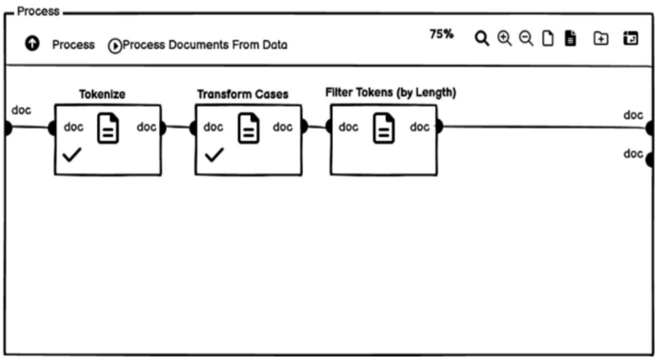

Figure 6. Process & Filter Tokenizing

The word cloud procedure comes next after the tokenizing phase is finished. The words that are commonly discussed or show up in the tweet data are identified using this word cloud process. Operators like WordList to Data, Sort, and Filter Example Range are added in order to carry out this operation.The word cloud procedure comes next after the tokenizing phase is finished. The words that are commonly discussed or show up in the tweet data are identified using this word cloud process. Operators like WordList to Data, Sort, and Filter Example Range are added in order to carry out this operation.

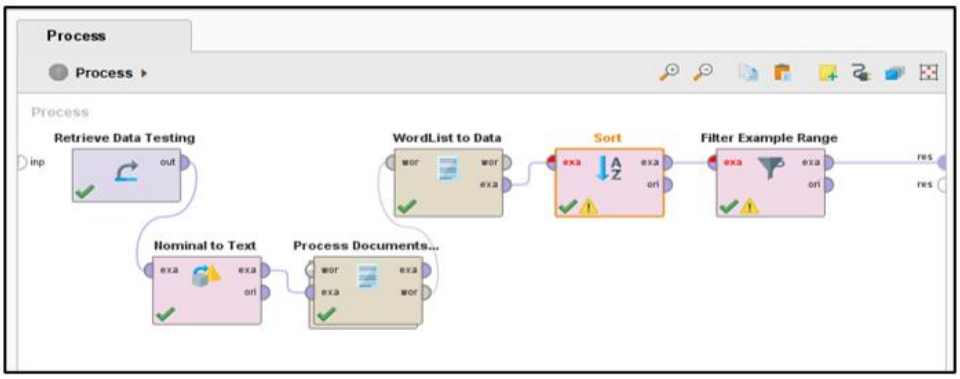

Figure 7 WordCloud Process

The top 5 commonly occurring words are displayed in the WordCloud results and are as follows:

Table 2 Total Word Occurrences

Text	**Pengulangan Kata**	**Persentase**
Gendut (Overweight	216	51%
Body shaming	82	20%
Kurus (Thin)	48	11%
Orang (People)	45	10%
Makan (Eating)	31	8%
Total	**422**	**100%**

Sentiment analysis of the data that has been cleaned up. The polarity analysis procedure, which is labeled using RapidMiner and uses the Extract Sentiment and Generate Attributes operators to classify the data into Positive (P) and Negative (N) (N). The sentiment toward the tweets is determined by testing the outcomes of the data analysis.

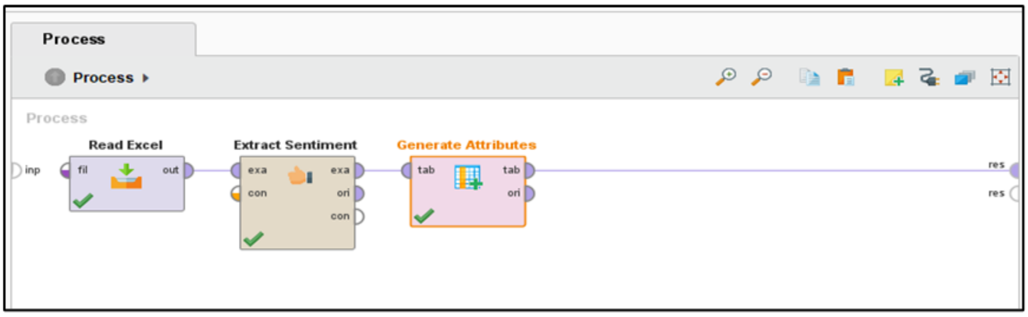

Figure 8. Sentiment Analysis Labeling Process

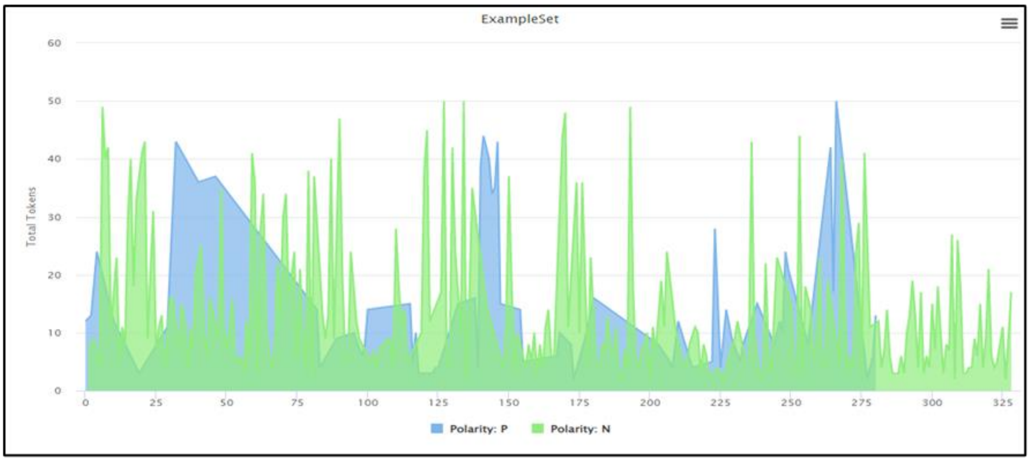

Figure 9. Data Visualization Results

NB :

Polarity Positive

Polarity Negative

N (Negatif) : 263 (80%)
P (Positif) : 66 (20%)

C. Unsupervised Bayes Classifier

One text classification technique based on keyword probability comparisons between training and test documents is the Naive Bayes Classifier approach. After going through multiple equality phases of comparison, the document with the highest likelihood is designated as the category for a new one. The classification procedure for the Naïve Bayes Classifier using Rapid Miner software is shown below:

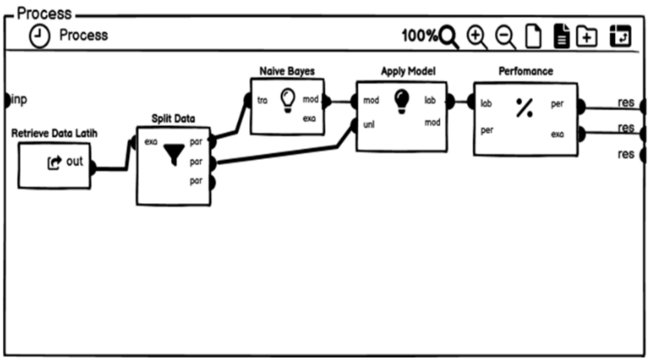

Figure 10. Unsupervised Bayes Classifier

The data that made it through the preprocessing stage and become clean data will now go through the classification procedure. The naive Bayes classification algorithm will be used to process the data. The machine will first be trained to identify patterns in the data or documents that are currently available, and it will then be able to classify the data into two groups: positive and negative classifications.

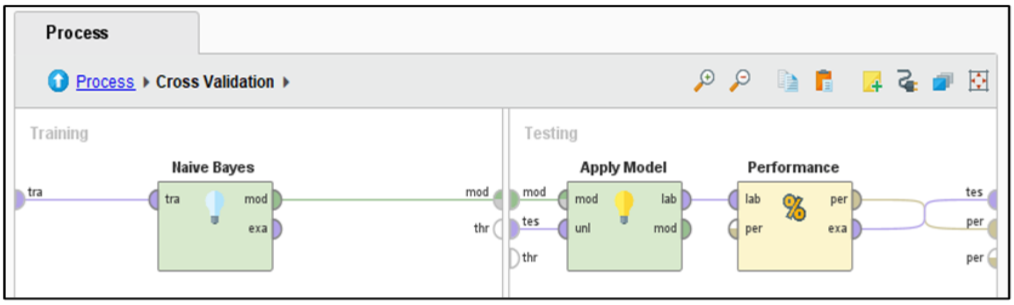

Figure 11. Naive Bayes Classifier Classification Process

Table 3. Results of Naive Bayes Classifier Algorithm Classification

Row No.	Polarity	prediction(Polarity)	confidence(P)	confidence(N)	Text
1	N	N	0.497	0.503	dan ada 2 orang tapi yg satu malah kebalikannya dulu kayaknya culun tapi sekarang cakep Wkwkw ini bodyshaming
2	N	N	0.497	0.503	Aku sangat berdosa ya sebab bodyshaming tapi tulahhh adoiii
3	N	N	0.497	0.503	3 taun gue pendem nih dulu dikatain dugong ternyata omongannya balik ke org yg ngatain wkkk jdi dugong lu makan tu...
4	N	N	0.497	0.503	lagi baca wp trs ada cast yg bodyshaming bilang buntalan arang bgsat ngakak bgt tp kasian
5	N	N	0.497	0.503	Woiii bodyshaming offsideee
6	N	N	0.497	0.503	Bodyshaming Vokabular
7	N	N	0.497	0.503	seminggu di cirebon kan turun 1kg aku d crb kira2 2 bulan brrti 8 minggu masi ada 7 minggu buat turun 7kg waitttt for it ...
8	N	N	0.497	0.503	Kek gada angin gada hujan whatsapp begini Maksudnya baik kali ya menurut dia ada baiknya memasang dp yang angl...
9	P	N	0.497	0.503	Aku terlihat gendut tergantung lihatnya dari angle mana dulu wkwkwk
10	N	N	0.497	0.503	beli sendiri lah kan rekening km gendut
11	N	N	0.497	0.503	Jadi keinget mbak ipar saya orangnya gendut karna efek KB bhkan smpe 80kgan pas dia sakit kebetulan saya yg jaga p...
12	N	N	0.497	0.503	NISHIMURA MAKSUDNYA MUKA AKU GENDUT GITU
13	P	N	0.497	0.503	aku malah pgn gendut
14	P	N	0.497	0.503	Yang bikin aku ngomong gpp gendut yg penting sehat itu karena udah capekkkk bgt disuruh2 orang buat ngurusin bada...

The outcomes of experiments conducted with the Naïve Bayes Classifier technique. The outcomes of the model testing on twitter data using a confusion matrix and the Naïve Bayes Classifier Algorithm are shown here.

Table View Plot View

accuracy: 80.55% +/- 1.53% (micro average: 80.55%)

	true P	true N	class precision
pred. P	2	0	100.00%
pred. N	64	263	80.43%
class recall	3.03%	100.00%	

Figure 12. Accuracy Value Results

1. *Accuracy*

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} x100\%$$

$$\text{Accuracy} = \frac{2 + 263}{2 + 263 + 0 + 64} \times 100\%$$

$$\text{Accuracy} = \frac{26500}{329} = 80{,}55\%$$

Table View Plot View

precision: 80.44% +/- 1.44% (micro average: 80.43%) (positive class: N)

	true P	true N	class precision
pred. P	2	0	100.00%
pred. N	64	263	80.43%
class recall	3.03%	100.00%	

Figure 13. Precision Value Results

2. *Precision*

$$Precison\ Positif = \frac{\text{TP}}{\text{TP} + \text{FP}} x100\%$$

$$Precision\ Positif = \frac{2}{2 + 0} \times 100\%$$

$$Precision\ Positif = \frac{200}{2} = 100\%$$

$$Precison\ Negatif = \frac{\text{TN}}{\text{TN} + \text{FN}} x100\%$$

$$Precision\ Negatif = \frac{263}{263 + 64} \times 100\%$$

$$Precision\ Negatif = \frac{26300}{327} = 80{,}43\%$$

Table View Plot View

recall: 100.00% +/- 0.00% (micro average: 100.00%) (positive class: N)

	true P	true N	class precision
pred. P	2	0	100.00%
pred. N	64	263	80.43%
class recall	3.03%	100.00%	

Figure 14. Recall Value Results

3. *Recall*

$$Recall\ Positif = \frac{\text{TP}}{\text{TP} + \text{FN}} x100\% \qquad Recall\ Negatif = \frac{\text{TN}}{\text{TN} + \text{FP}} x100\%$$

$$Recall\ Positif = \frac{2}{2 + 64} x100\% \qquad Recall\ Negatif = \frac{263}{263 + 0} x100\%$$

$$Recall\ Positif = \frac{2}{66} = 3{,}03\% \qquad Recall\ Negatif = \frac{26300}{263} = 100\%$$

Analysis Outcomes

The breakdown of the original data, or training data, can be outlined as it lowers through several stages, from crawling to classification using the Naïve Bayes Classifier algorithm, after completing sentiment analysis using RapidMiner. This is its historical data:

- **Data cleansing and crawling**

Crawled data totaled 1000 Twitter data points, made up of training or raw data that was acquired via RapidMiner. Following the cleaning procedure, 329 Twitter data points worth of testing or test data were acquired.

- **Tokenizing**

Using testing data, this technique generates a word cloud result that displays the frequency of words such as "Overweight" (51%), "Body Shaming" (20%), "Thin" (11%), "People" (10%), and "Eating" (8%).

- **Testing the Algorithm of Naïve Bayes Classifier**

The following results from the algorithm testing method were obtained: 80.55 percent accuracy, 100 percent positive precision, 80.43 percent negative precision, 3.03 percent positive recall, and 100 percent negative recall."

CONCLUSION

The research findings allow for the following conclusions to be made in light of the steps of the process that were covered in the previous chapter as well as the outcomes of testing and analysis:

1. In this study, testing data comprising 329 tweets was obtained based on training data gathered from 1000 tweets. Positive and negative feelings involving body shaming on Twitter were identified by hand labeling using Microsoft Excel and categorizing the dataset's data visualization using RapidMiner in order to evaluate the sentiment of the tweet data. Data visualization derived from the sentiment analysis shows a 20% positive sentiment value and an 80% negative sentiment value.

2. The following values were obtained based on the Naïve Bayes Classifier test results: 80.55 percent accuracy, 100 percent positive precision, 80.43 percent negative precision, 3.03 percent positive recall, and 100 percent negative recall

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