

CYBERBULLYING SENTIMENT ANALYSIS OF FACEBOOK COMMENTS USING THE CLASSIFICATION METHOD SUPPORT VECTOR MACHINE

Rafli Muhammad Kamal¹, Ednawati Rainarli²

^{1,2}Informatics Engineering Study Program

Faculty of Engineering and Computer Science Indonesian Computer University

Jl. Dipati Ukur 114 Bandung

E-mail: raflimkamal97@email.unikom.ac.id¹, ednawati.rainarli@email.unikom.ac.id²

ABSTRACT

Along with the widespread use of Facebook as social media, of course the more diverse comments written by someone in a post. Sometimes Facebook users unwittingly write comments that contain elements of bullying. Of course it will have a bad impact on himself and others, therefore there needs to be an analysis related to Facebook comments. Machine learning approach that can be used to detect cyberbullying is sentiment analysis. In this study, we will discuss sentiment analysis using the Support Vector Machine (SVM) method. The process is to classify positive (not bullying) or negative (containing bullying) sentiments. In the preprocessing step a word normalization process is added with the aim to overcome the use of non-standard words from comments to be processed. For accuracy testing, 2 tests are performed. Testing I uses 100 training data and 100 test data and Testing II uses 100 training data and 50 test data derived from facebook user comment data. The results of accuracy testing conducted show that SVM can have a fairly high percentage level in the case of sentiment analysis can reach 96% using the RBF kernel function. It can be concluded that the Support Vector Machine classification method works well in the case of cyberbullying sentiment analysis on facebook comments.

Keywords : sentiment analysis, comments, preprocessing, TF-IDF, support vector machine, RBF

1. PRELIMINARY

Facebook is one of the most widely used social media in Indonesia. The problem that often occurs is cyberbullying actions that appear on Facebook. Not many Facebook users realize that the comments or comments written to a person or group are acts of bullying. Facebook users are free to post status and comment is one of the reasons for the emergence of content that is injuring and resulting in harassment (bullying) on social media.

How to detect comments that contain elements of bullying can use a machine learning approach that is by sentiment analysis. Sentiment analysis is needed to

filter out comments on social media. The process carried out in sentiment analysis is to classify information into positive sentiment classes and negative sentiment classes. Information will be classified into positive classes if the information submitted is of good value or agrees to something. On the other hand, information is classified into negative class if the information submitted is not good or not agree [1]. To classify comments, we need a machine learning approach that can separate between comments that contain cyberbullying and do not contain cyberbullying. Therefore, the support vector machine algorithm was chosen for this research.

In previous studies that are useful in supporting the implementation of related research is research on sentiment analysis using the Support Vector Machine method by Petrik [2]. Other studies discussing the categorization of Indonesian texts by Wulandini and Nugroho, obtained the SVM algorithm has the highest accuracy of 92.5% compared to other algorithms such as K-Nearest Neighbors, Naïve Bayes Classification, Information Fuzzy Networks [3].

It was concluded that the use of the Support Vector Machine (SVM) method provides the best accuracy results compared to other methods. Based on that, this research will use the Support Vector Machine method to detect sentiments and find out the accuracy of the method used.

2. REVIEW LITERATURE

2.1 Harrasment(Bullying)

As the times evolve, technology also develops. The development of technology has an influence on social life. As in the act of bullying. Initially the act of bullying attacks physically and psychologically directly, but now these actions can be carried out in cyberspace known as cyberbullying. Cyberbullying is an unpleasant action that is done intentionally and continuously through electronic texts [4].

Cyberbullying is one form of malicious attacks to give satisfaction or pleasure of the offender by degrading others. Women are more involved in cyberbullying, both as perpetrators and as victims. Where 50% of victims of cyberbullying generally do not know the identity of the bullies even though only

gender. Cyberbullying is an action that can attack psychological, emotional, and social trauma [5].

This is a very serious problem when cyberbullying becomes more dangerous than bullies in general. Because the effects are more dangerous when feelings of fear and depression then turn into frustration and anger, even severe can cause victims to commit suicide. The choice of words spoken is one of the keys to whether someone leads to acts of bullying or not [6].

2.2 Text Mining

Text mining is a scientific discipline that focuses on information search, data mining, machine learning, statistics, and linguistic computing [7].

Data sources used in text mining are collections of texts that have an unstructured or semi-structured format. The purpose of text mining is to get useful information from a collection of documents.

Some main stages of the process of text mining, namely the initial processing of text (text preprocessing), text transformation (Text transformation) or (Feature Generation), feature selection (feature selection), and discovery of text patterns or data mining (pattern discovery).

2.2.1 Text Preprocessing

Preprocessing is the initial stage of text mining to change data in accordance with the required format. This process is carried out to explore, process and manage information and to analyze the textual relationship of structured and unstructured data [8]. The preprocessing process also aims to make the data used have smaller dimensions and structured, so that it can be processed further. The stages of preprocessing include: case folding, cleansing, language normalization, convert negation, stopwords removal, tokenizing.

a) Case Folding

The initial stage is case folding which is the preprocessing stage carried out to homogenize the characters in the data (documentation / text). Because not all text documents only use capital letters, all letters can be converted to uppercase or lower case [lower case] [1]

b) Cleansing

Cleansing is a process for cleansing words other than the characters 'a' to 'z' and excess spaces will be removed. Word cleaning aims to reduce noise. To overcome excess space after cleansing, remove excess spaces from before and after words (remove whitespace).

c) Language Normalization

In the preprocessing stage, language normalization is performed on non-standard words. This stage aims to restore the writing form of each word in accordance with the KBBI. This process is done by matching each word in the training data document and test data with the words in the dictionary [9].

d) Convert Negation

Negative words, will change the sentiment value of a comment. When many negation words are odd, the sentiment of that comment will change. The word "no" will be used to replace negated words outside the KBBI dictionary [10]. To overcome excess space after convert negation, remove excessive spaces from before and after words (remove whitespace).

e) Stopword Removal

Stopword Removal aims to eliminate words (terms) that are considered unable to influence in determining a particular category in a document. Before the stopword removal process is performed, words are included in the stopword. Stopword is a list of common words that have no significance and are not used. In this process common words will be deleted to reduce the number of words stored by the system.

f) Tokenizing

Tokenizing is the process of cutting a document into small pieces that can be chapters, sub-chapters, paragraphs, sentences, and words (tokens). This process will eliminate whitespace.

2.3 TF IDF Weighting

Weighting Term Frequency-Inverse Document Frequency (TF-IDF) is the method used to calculate bobotan s ach word has been extracted . The TF-IDF weighting model is a method that integrates the term frequency (tf) and inverse document frequency (idf) models , where the term frequency (tf) is the process of counting the number of occurrences of terms in one document and inverse document frequency (idf) is used to calculate the term which appears in various documents (comments) which are considered as general terms , which are considered not important [11] . The initial process carried out in weighting TF-IDF is done by calculating the term frequency . Where t indicates the term in document d which serves to show the appearance of the term t in document d . It is influential in weight terms that will be increasingly high when a lot of terms that appear in a document. The value of tf will be calculated weight by the formula weighting term frequency (W_{tf}) . The formula is shown in Equation 1

$$W_{tf, d} = \begin{cases} 1 + \log_{10} tf_{t,d} & \text{if } tf_{t,d} > 0 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

The number of words that appear on the document, is generally the value of the term frequency of words that are not important. To avoid weighting on unimportant words , document frequency weighting is used to intend to count the number of documents containing term t .

From the term value on each document that has been found, the reverse process of the document frequency weighting will be carried out . This

weighting process is called inverse document frequency, which states that the frequency of the low term in many documents will give the highest weight. This calculation is shown by Equation 2.

$$idf_t = \log \frac{N}{df_t} \quad (2)$$

Where :

idf_t = inverse weight of the value df

N = number of documents in the document

df = number of documents containing term

Calculation of TF-IDF weighting is a multiplication which is done from weighting term frequency with inverse document frequency. This is shown in Equation 3.

$$W_{t,d} = W_t t f_{t,d} \times idf_t \quad (3)$$

Information:

$W_{t,d}$ = word weight in each document

$t f_{t,d}$ = number of occurrences of t in document d

idf_t = inverse weight of the value df

$W_{t,d}$ = TF-IDF weighting

2.4 Support Vector Machine

Support Vector Machine (SVM) is a technique for making predictions, both in the case of classification or regression. The SVM method has a basic principle of linear classifier, which is a case of classification that can be separated linearly, but the developed SVM can work with non-linear problems by incorporating the concept of the kernel in high-dimensional space.

In high-dimensional space, hyperplane will be able to maximize the distance (margin) between data classes. The Support Vector Machine (SVM) method is rooted in statistical learning theory which can provide better results than other methods [2].

SVM can work with non-linear data using the kernel approach to the initial data set features. The kernel function used to map the initial dimensions (lower dimensions) of data sets to new dimensions (higher dimensions).

The concept of SVM is the search for the best hyperplane that functions as a data separator from two classes in the input space. The best separating hyperplane is the hyperplane located in the middle between two sets of objects from two classes. The best hyperplane can be searched by maximizing the margin or distance of two sets of objects from two different classes.

It can be assumed that the two classes can be completely separated by a hyperplane (linear separable). However, in general the two classes in the input space cannot be completely separate (non linear separable). To overcome this problem SVM was reformulated by introducing the margin method [12]. As in Figure 1.

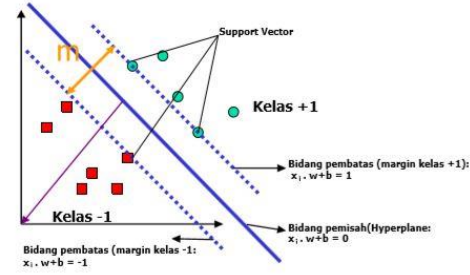


Figure 1. Margin Hyperplane

2.4.1 Linear Separable Data Classification

Linear Separable data is data that can be separated for example $\{x_1 \dots x_n\}$ is the data set $\{+1, -1\}$ is the label of the class from data to x_n . In Figure 1. can be seen various alternative fields that can separate all data sets according to their class. However, the best separator field can not only separate data but also have the largest margins.

The training data is declared $(y_i; x_i)$ dimana $i = 1, 2, \dots, N$, dan $x_i = (x_{i1} x_{i2} \dots, x_{iq})^T$ where $i = 1, 2, \dots, N$, and is an attribute (feature) of the i training data set, $y_i \in \{-1, +1\}$ declares the class label. The SVM linear classification hyperplane [3] is denoted:

$$w \cdot x_i + b = \quad (4)$$

Information :

w and b = model parameters.

$w \cdot x_i$ is an inner product between w and x_i

If x_i falls into -1 then it satisfies the following inequality:

$$w \cdot x_i + b \leq -1 \quad (5)$$

If x_i falls into $+1$ then it satisfies the following inequality:

$$w \cdot x_i + b \leq +1 \quad (6)$$

if data in class -1 (x_a) is in the hyperplane, the equation will be fulfilled to be denoted as follows:

$$w \cdot x_a + b = 0 \quad (7)$$

$+1$ class data (x_b) will satisfy the following equation:

$$w \cdot x_b + b = 0 \quad (8)$$

By reducing the equation as follows: :

$$w \cdot (x_b - x_a) = 0 \quad (9)$$

$x_b - x_a$ is a parallel vector in the hyperplane position and directed from x_a to x_b , then the direction w is perpendicular to the hyperplane when the inner product is zero.

The formula for giving the label -1 for the first class, and $+1$ for the second class as follows:

$$Y = \begin{cases} +1, & \text{jika } w \cdot z + b > 0 \\ -1, & \text{jika } w \cdot z + b < 0 \end{cases} \quad (10)$$

Hyperplane for class -1 (dashed line) is data in a support vector that satisfies the equation:

$$\mathbf{w} \cdot \mathbf{x}_b + \mathbf{b} = -1 \quad (11)$$

Hyperplane for class +1 (dashed line) satisfies equation:

$$\mathbf{w} \cdot \mathbf{x}_b + \mathbf{b} = +1 \quad (12)$$

Margin can be calculated as :

$$\mathbf{w} \cdot (\mathbf{x}_b - \mathbf{x}_a) = 2 \quad (13)$$

To find the best hyperplane margin (distance) located in the middle of two equal class boundary planes by maximizing the margin or distance between two sets of different class objects. Then the margin can be calculated with:

$$\|\mathbf{w}\| \mathbf{x} \mathbf{d} = 2 \text{ or } \mathbf{d} = \frac{2}{\|\mathbf{w}\|} \quad (14)$$

2.4.2 Non Linear Separable Data Classification

To solve non-linear problems, SVM is modified by including kernel functions. In non-linear SVM, data x is first mapped by the function $\Phi(x)$ to a higher dimensional vector space. Hyperplane that separates the two classes can be constructed. Furthermore, the function Φ maps each data in the input space to a new vector space with a higher dimension (dimension 3), so that the two classes can be linearly separated by a hyperplane.

Furthermore, the learning process in SVM in finding support vector points depends only on the dot product (multiplication point) of the data that has been transformed into a new dimension of higher space, namely $\Phi(x_i) \cdot \Phi(x_j)$. Because these Φ transformations are generally unknown, and are very difficult to understand easily, the dot product calculation can be replaced by the kernel(x_i, x_j) function which implicitly defines the transformation Φ . This is called the Kernel Trick, which is formulated:

a. Linear

$$K(x, x_i) = x_i^T x \quad (15)$$

b. Polynomial Kernel

$$K(x, x_i) = (x_i^T x + 1)^d \quad (16)$$

c. RBF

$$K(x, x_i) = \exp\{-\gamma \|x - x_i\|^2, \gamma > 0\} \quad (17)$$

d. Sigmoid Kernel

$$K(x, x_i) = \tanh[K + x_i^T x + \theta] \quad (18)$$

Using the kernel function will determine the feature space where the classifier function will be sought. As long as the kernel's function is legitimate, SVM will operate correctly even though it doesn't know what map to use, so it's easier to find the kernel's function than to find what map is appropriate

for mapping from input space to feature space. In the application of the kernel method, it is not necessary to know what map is used for one by one data, but it is more important to know that the dot product (dot product) of two points in the feature space can be replaced by kernel functions.

And predictions on dimensional data sets with new features formulated :

$$f(\phi(x)) = (\text{sign}(\mathbf{w} \cdot \phi(x) + \mathbf{b})) \quad (19)$$

$$= \sum_{i=1, x_i \in SV}^n (\text{sign}(\alpha_i y_i \phi(x) \cdot \phi(x_i) + \mathbf{b}))$$

$$= \sum_{i=1, x_i \in SV}^n (\text{sign}(\alpha_i y_i K(x, x_i) + \mathbf{b}))$$

3. RESEARCH METHODAN

The steps undertaken in this study :

- Identification of problems
- Data collection
- Process Analysis
- Testing
- Withdrawal of Conclusions

4. RESULTS AND DISCUSSION

To see the use of the support vector machine method in the case of sentiment analysis, the following is the analysis of the process of cyberbullying sentiment analysis on Facebook fanpage comments with the support vector machine classification method, which includes data collection, preprocessing, and then support vector machine verification.

The stages used to determine the existence of sentences containing bullying in the text in this study are divided into two stages, namely the training and testing stages.

The following is an overview of the stages of the process to be carried out in Figure 2.

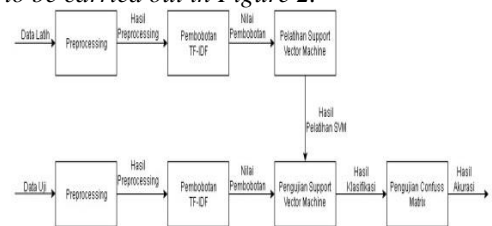


Figure 2. Process Stage

4.1 Data Entry Analysis

Input data used in this study are comments on facebook from predetermined facebook posts. Input data that is 150 comment data that will be used, which consists of, 100 comment data as training data, and 50 comment data into test data.

The data used in this research consists of two types of data; namely training data and test data.

4.2 Preprocessing Analysis

Preprocessing analysis is the initial stage and one of the important steps in the classification of a text. The preprocessing stages that will be carried out in this research are Case folding, Cleansing, Language Normalization, Convert Negation, Stopword Removal, Tokenisation. This preprocessing is done on training data that becomes input data, the results of preprocessing can be seen in Table 1.

Table 1 Preprocessing Results

Words
wasit indonesia sulit fokus sudah dapat tekanan semoga mental wasit jugabisdiperbaiki padahal fase grup mantap

4.3 TF-IDF Weighting Analysis

The initial process is to calculate the term (single word) on each document, so that it will get the term frequency. Next is calculating df, because df is the number of documents where the term appears. After obtaining the df value, the idf calculation is performed.

Taken an example in the word "wasit". Then obtained many documents (N) = 7, and $df = 3$. Then the calculation is as follows.

$$idf_t = \log\left(\frac{7}{3}\right) = 0,368$$

Furthermore, to get the term weights, then do the calculation of tf and idf.

Obtained $tf = 3$, and $idf = 0.477$. Then the calculation becomes as follows.

$$Wt = 3 * 0.368 = 1.104$$

So the word "wasitu" has a weight of 1.104.

4.4 Support Vector Machine Classification

At the stage classification Support Vector Machine training phase is done to get hyperplane obtained from training data that has been entered then the data hyperplane tersebut entered into the database. The next step taken is the testing phase. Test data is entered through the same process as training data, namely the preprocessing process, TF-IDF weighting, then the results of this test are sentiment classification in the form of facebook comments from the entered test data. Then for testing the system the confuss matrix method is performed. The results of these tests will produce accuracy from the Support Vector Machine method.

4.4.1 Support Vector Machine Training

SVM training aims to find vectors a , W values and constants b to get the best hyperplane. In this study, the data used as training is comment data. In the SVM training process, each classification model is trained with two i -th grade and j -class.

Input data that will be used for the training process are data from 2 different classes that have been through preprocessing. In accordance with the

input data, the comment data are given positive and negative classes, then labeled class 1 or -1 where class -1 is a negative class while class 1 is a positive class.

$$f(\phi(x)) = (\text{sign}(w \cdot \phi(x)) + b) \\ = \sum_{i=1, x_i \in SV}^n (\text{sign}(\alpha_i y_i K(x, x_i)) + b)$$

where $i = 1, 2, 3, \dots, n$ = number of support vectors.

Then the field of training is obtained :

$$f(x_{\text{testing}}) = (\text{sign} (0,255(0,645) + 0,122(0,05311) + 0,243(0,24446) - 0,060(0,2876) - 0,102(0,21687) - 0,123(0,24654) , K(x_i x_{\text{testing}})) + 0,125)$$

4.1.2 Support Vector Machine Testing

After getting the values of a and b as the feature model, and the gamma parameter value of 0.5 (γ) from the training process, then testing the test data into classes +1 or -1 with the feature model that has been obtained. The data used for testing is the training data P1, P2, P3, P4, P5, P6 as the results of the training data.

determine which class the comment has been tested using the hyperplane function.

$$f(x_{\text{testing}}) = (\text{sign} \sum_{i=1}^n \alpha_i y_i K(x_i x_{\text{testing}}) + b)$$

Then

$$f(x_{\text{testing}}) = (\text{sign} (\alpha_1 y_1 K(x_1, x_{\text{testing}}) + \alpha_2 y_2 K(x_2, x_{\text{testing}}) + \alpha_3 y_3 K(x_3, x_{\text{testing}}) + \alpha_4 y_4 K(x_4, x_{\text{testing}}) + \alpha_5 y_5 K(x_5, x_{\text{testing}}) + \alpha_6 y_6 K(x_6, x_{\text{testing}}) + b) \\ = (\text{sign}(0,255(1) + 0,122(0,05311) + 0,243(0,24446) - 0,060(0,02876) - 0,102(0,21687) - 0,123(0,24654) + 0,125) \\ = \text{sign}(0,0819) \\ = +1$$

After one class comments through the testing phase, it produces a hyperplane +1 function that is (positive).

4.1.3 Accuracy Testing

Accuracy test results are an illustration of the testing scenarios conducted, namely testing in the use of variable values in the support vector machine algorithm as well as testing the accuracy of the resulting text detection. Tests carried out using values ranging from 0.1 to 1.

1. Accuracy Testing I with 100 data training dan 100 data testing (same with data training). The results of the scenario can be seen in Table 2.

Table 2 Accuracy Testing Results I

γ	Accuracy	Precision	Recall	F-measure
0,1	0,53	0	0	0
0,2	0,71	0,50	0,38	0,55
0,3	0,92	0,97	0,85	0,90
0,4	0,96	0,97	0,94	0,96
0,5	0,97	0,97	0,96	0,97
0,6	0,98	0,98	0,98	0,97
0,7	0,98	0,98	0,98	0,97
0,8	0,99	0,97	0,99	0,98
0,9	0,99	0,97	0,99	0,98
1	100	100	100	100

2. Accuracy testing II with 100 the data train and 50 Data test (different from the training data) . The results of the scenario can be seen in Table 3.

Table 3 Accuracy Testing Results II

γ	Accuracy	Precision	Recall	F-measure
0,1	0,52	0,27	0,52	0,35
0,2	0,60	0,69	0,60	0,53
0,3	0,64	0,69	0,64	0,60
0,4	0,68	0,70	0,68	0,66
0,5	0,65	0,65	0,64	0,62
0,6	0,64	0,65	0,64	0,63
0,7	0,64	0,65	0,64	0,63
0,8	0,67	0,66	0,67	0,63
0,9	0,69	0,67	0,69	0,67
1	0,75	0,73	0,75	0,74

Based on the results of testing accuracy I in Table 2 the optimal value obtained with training data of 100 training and 100 test data (the same as training data) and then using gamma 1 value produces 100% accuracy. While based on the results of accuracy testing II in Table 3, the optimal value obtained with 100 training data and 50 test data (different from training data) and then using gamma 1 value produces a 75% drainage .

Cyberbullying sentiment analysis with the Support Vector Machine method with RBF Kernel was tested for accuracy 2 times. Testing accuracy I used 100 training data and 100 test data (same as training data) and accuracy testing II used 100 training data and 50 test data (different from training data). Research has been done by Imelda and Affandes [13]. From the results of trials conducted both, The application shows stable accuracy in the range of values of $0 \leq C \leq 3$ and $0.01 \leq \gamma \leq 10$ on the data that has not been selected features and stable accuracy in the range of values $0 \leq C \leq 300$ and $0.01 \leq \gamma \leq 10$. With the achievement of good accuracy then , the use of parameters can make accuracy stable and this result can be applied to help Twitter users to filter ad tweets contained in their Twitter accounts [13]. Based on the results of testing evaluations with calculations performed with the values of precision, recall and F-measures listed in the first accuracy test in Table 2 and the second accuracy testing Table 3. resulting in a significant difference in value. The

accuracy value produced in the accuracy testing I is in the range of 53% to 100%. While in accuracy testing II accuracy values are in the range of 52% to 75%. These results indicate that the amount of test data used can affect the level of accuracy generated to detect text. Also based on research above the use of gamma parameters from the range 0.1 to 1 can make an influence on accuracy, which can make stable accuracy.

5. Conclusions and Suggestions

5.1 Conclusions

Bullying text detection research on social media by implementing Support Vector Machine on Facebook comments in Indonesian language has several shortcomings including:

1. Data set taken is Facebook comment data that has different emoticons with Twitter / does not have a dictionary so it cannot be processed further.
2. The number of typo words so that an error occurs in some preprocessing processes so that it is processed because it is not detected in stopwords.
3. There is no official source or reference in the list of words that contain Indonesian language bullying.
4. The preprocessing stage influences sentiment analysis because it can produce word features that are useful during the classification process.
5. Testing the classification of sentiment analysis using 150 documents, of which 100 documents are used as training data and 50 documents as test data, yielding the highest accuracy of 75% using gamma values of 0.5 and C 1.

Based on the research that has been done, it can be concluded that the application of the Support Vector Machine method is a method that has good accuracy to be used in the case of sentiment analysis.

5.2 Suggestions

Suggestions for developing bullying text detection on Indonesian-language social media from this study are:

1. The data set used can be added to find out whether there is an increase in machine learning. Data sets can be replaced from other social media and typo languages can be overcome so as to minimize errors in the preprocessing stage.
2. Changing the method used to be able to compare the method's performance in detecting Indonesian language bullying texts.

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