Decision Making Framework Based On Sentiment Analysis in Twitter Using SAW and Machine Learning Approach

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***Abstract*— One type of social media that is often used is Twitter. The development of social media is so fast that even users reach 326 million and produce 500 million tweets every day in July 2018. Users can send, change, and read short messages which have been called tweets. Tweets can contain facts or opinions so it is very beneficial to be analyzed. The results of this analysis can be in the form of stock market predictions, elections, reaction events or news and measuring subjectivity. The activity of analyzing tweet is a series of sentiment analysis activities. However, the results of sentiment analysis are cumulative in percentage of tweet polarity and only provide a overview for decision making. So, the intuitive aspect still plays a role in deciding the results of the Sentiment Analysis. Therefore, there is a need for more specific modeling of sentiment analysis results. In the decision making phase, the results of the Sentiment Analysis are still in the Intelligence phase or can be called the Problem Discovery. To proceed again to the Design phase until with a Choice, it is necessary to have a Decision Support System (DSS). In this study trying to propose a decision making framework based on the results of sentiment analysis from the Tweet dataset. Sentiment analysis is built using the machine learning approach. Furthermore, the results of this study indicate that the SAW method can accept the input polarity of the number of tweets and produce alternative decision weights.**

Keywords—Decision Support System, Sentiment Analysis, Simple Additive Weigthing, Twitter

I. INTRODUCTION

Social media creates virtual boundaries among users where people express their opinions and develop relationships through posts, comments, messages and likes columns. One type of Social Media is Twitter which is developing very fast on an online platform. Twitter is growing rapidly online and even in July 2018 has 326 million active users and 500 million tweets per day [1]. Someone can create, send, change and read short messages called tweets. Twitter is widely used by people to report several activities that have been carried out. In addition, Twitter also provides a collection of several tweets that can be accessed in general.

A large number of tweets is very potential for analysis. This involves the content of opinions contained in the tweet. Opinion Analysis can be called Sentiment Analysis. Sentiment Analysis is part of Natural Language Processing which aims to classify text based on the polarity setiment. This analysis becomes a good tool in processing and analyzing opinions in large numbers [2]. This activity is very useful in predicting certain areas such as stock market predictions, general elections, measuring event or news reactions, and measuring subjectivity. The results of Sentiment Analysis can be used as a reference for the company or manager level to make decisions.

This sentiment classification also uses machine learning approach in classifying tweet polarity. The implemented algorithm such as Naive Bayes, Decision Tree, Logistic Regression, and Support Vector Machine [2] [3]. This machine learning approach requires training data that will produce a model. After the model is obtained, the system can make predictions or classifications of newly recognized data. This approach has the advantage of finding knowledge from data provided to computer programs. So, the computer seems to study the data provided. Then, when the computer has found the loaded knowledge, the data provided is not used. In other words, program developers do not need to do programming explicitly to declare existing knowledge.

Sentiment Analysis can also be a major component in decision support systems that are able to efficiently support companies in managing promotional and marketing activities on various social media channels [4]. The results have been obtained from the Sentiment Analysis are still in the form of cumulative visualization of the number of existing sentiments. For decision makers consider this very important to determine the next decision. However, the cumulative results only provide an overview for decision making. So, the intuitive aspect still plays a role in deciding the results of the Sentiment Analysis. Therefore, there is a need for more specific modeling of sentiment analysis results. In the decision making phase, the results of the Sentiment Analysis are still in the Intelligence phase or can be called the Problem Discovery. To proceed again to the Design phase until with a Choice, it is necessary to have a Decision Support System (DSS). This will provide decision support for decision makers so that it is more helpful in making decisions because there are several alternative decisions that are ready to be chosen.

One of technique for modeling several decision alternatives is SAW (Simple Additive Weigthing). SAW is the most frequently used techniques for solving spatial decision analysis problems. Decision makers directly give a relatively important weight for each attribute [5] [6]. This method is widely used in DSS and determines the best alternative by giving a weighting. Weighting values in alternative decisions requires a matrix. SAW can handle the Multiple Criteria Decision-Making (MCDM) problem because the linear additive function can represent the preferences of decision makers [7]. Alternative decisions that have been sorted based on the final score can help decision makers to decide by choosing an alternative decision that exists.

In this study, proposed a decision making framework based on the results of sentiment analysis from the Tweet dataset. Searching for tweet topics is then sentiment analysis using several classifiers such as SVM, Naive Bayes, Decision Tree, and will produce cumulative sentiments. The classifier is selected based on the best accuracy. These results are used as criteria and the weighted criteria are calculated using the SAW method. The results of calculations with SAW produce a ranking of several alternative decisions. Decision makers can choose alternative decisions with the greatest value.

II. Sentiment Analysis

Sentiment Analysis can be called opinion mining. Using language computing and data mining to convert data into information [8]. Sentiment analysis can detect a condition of emotional person, behavior, and opinion based on existing tweets or text. The results of this detection are positive, negative or neutral labels. However, to achieve this, massive training is needed and the data is not structured. This is a challenge to change unstructured data into structured data.

Sentiment Analysis has spread in every day from consumer products, services, health care, and financial services to social events and elections. This is very important because the analysis of opinion will produce a picture for reference decision making [9]. In addition, the existence of this sentiment analysis can measure market responses to newly launched products.

III. Decision Making Phase

Decision making is the process of selecting one of the many guidelines available to achieve the desired goals [10]. The decision making process goes through several phases shown in Fig 1.

In Fig. 1, Simon's model is proposed to present the phase of the decision making process. The first is the intelligence phase, which is the identification phase of the goals and objectives of the organization related to a problem [11]. A decision maker needs to define the problem and its characteristics. The problem domain must be traced to a basic problem. In this phase, decision makers must also examine real conditions and try to identify opportunities properly.

The second phase is the design phase. This phase seeks to define and model the system as a system representation. It also needs to be defined the relationship of some of the variables specified. This phase also tries to model alternative decisions that will be chosen by decision makers. The design or model that is built can apply several approaches or methods such as SAW, TOPSIS, AHP, Promithe, and so on. This model is also a search for solutions that will be offered to develop alternative decisions that have weighted values. In this phase DSS has a role to model the preferences of the problems that have been defined.

The third phase is the selection phase. The use of DSS will produce several alternative decisions that have been sorted based on the results of the assessment. This alternative decision list is a reference for decision makers to choose. This phase displays the results of alternative decisions that have been ordered and the decision maker is faced with these choices. This has the effect that decision makers will choose alternative decisions that are not intuitive but more objective.

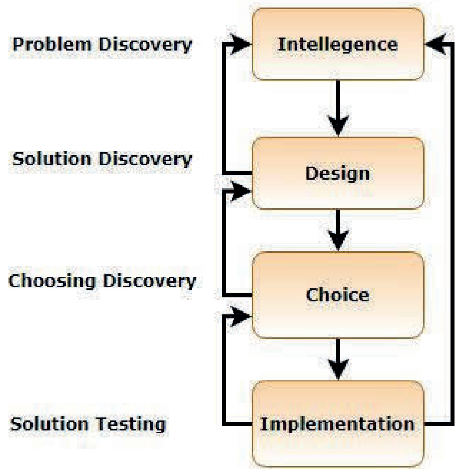

Fig. 1. Decision Making Phase

The fourth phase is implementation. This phase seeks to implement alternative decisions that have been chosen by decision makers. The alternative chosen is applied and observed the resulting impact. These observations make feedback in the DSS and try to revise the shortcomings of the DSS that will be built. Feedback can go back to the previous phase or directly to the initial phase.

IV. Simple Additive Weighting (SAW)

Decision makers can directly fill the relative weights into each criterion. The final score is obtained by multiplying the weight value of each criterion and its alternative value [5], [6]. The SAW calculation is shown in equations 1 and 2 where there is a normalization matrix phase which is shown in the final score [5].

Normalization for positive criterion

$$n_{ij} = \frac{g_{ij}}{g_{max}} \quad i = 1, \dots, m \; j = 1, \dots, m \tag{1}$$

Normalization for negative criterion

$$n_{ij} = \frac{g_{min}}{g_{ij}} \quad i = 1, \dots, m \; j = 1, \dots, m \tag{2}$$

$$Final\ Score = \sum(w_{gij} \times n_{ij}) \sum w_{gij} = 1 \tag{3}$$

where g_{ij} is the criterion value; g_{max} is the maximum value of each positive criterion; g_{min} is a minimum value of negative criteria; and n_{ij} is the normalized value.

V. Methodology

In this study, a general picture of decision making that refers to sentiment analysis is illustrated in Fig. 2. This general description is the framework proposed in this study to be able to produce an alternative decision sequence that has a weight value.

The proposed framework has 4 stages as follows:

1. Crawling Tweet

This initial stage attempts to retrieve tweets based on search keywords that have not been labeled to be labeled. This search keyword is an alternative that will be given a weight value.

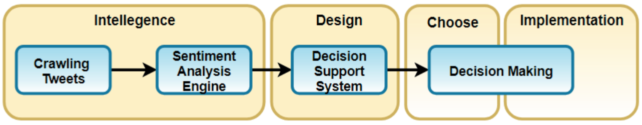

Fig. 2. Decision Making Based On Sentimen Analysis

So, to produce alternative decisions, you need a few keywords to get the desired tweet. Tweets obtained obtained a maximum of 20 pieces for each keyword. So, each alternative decision has 20 tweets.

2. Sentiment Analysis Engine

At this stage, the results of crawling tweets in the form of a collection of tweets per alternative decision will be classified. For example, 20 tweets found from each keyword will be classified with polarity such as positive, negative and neutral. After all tweets are classified, finally the percentage of each polarity is obtained. So, each alternative decision has a positive, neutral, and negative process. The structure of the Sentiment Analysis Engine proposed in this study is shown in Fig. 3

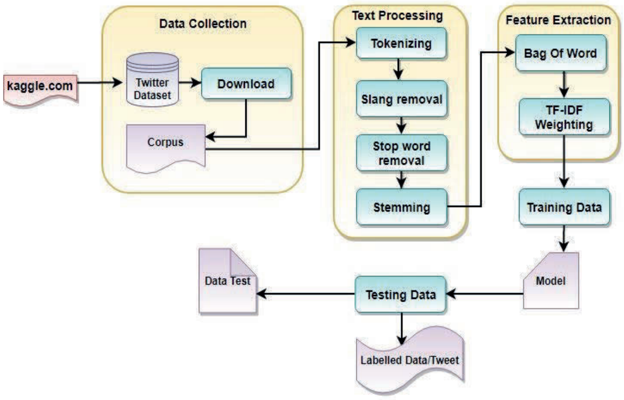

Fig. 3. Sentiment Analysis Engine Architecture

3. Decision Support System

At this stage there are a number of alternative decisions that will be weighted. The input in this calculation is a percentage of tweet polarity for each alternative decision. Positive, negative, and neutral percentages are used as criterion values at this stage. Weight calculation at this stage uses SAW. This calculation results in a final score for each alternative decision. All alternative decisions are sorted by final score. The SAW calculation process is shown in Fig 4.

4. Decision Making

At this stage an alternative decision sequence has emerged based on the final score which is the result of calculations with SAW. Furthermore, decision makers are recommended to choose alternative decisions that have the greatest value. Then, the decision maker applies the selected alternative decision. Furthermore, there is feedback either in the form of a quisoner or an interview with the decision maker who has implemented the alternative decision. This feedback is used as a validation of the proposed framework according to Fig. 2

In Fig. 3 there is the architecture of the Sentiment Analysis Engine (SAE). This architecture contains several main phases as follows:

1. Data Collection

This stage attempts to collect the labeled tweet data. This collection of tweets data was found from kaggle.com. This collected tweet data is about English tweets that have been labeled with positive, negative and neutral polarity. Furthermore, this tweet data collection is used as a dataset to become a corpus so that Text Preprocessing can be performed.

2. Text Preprocessing

At this stage trying to get a clean collection of words or terms. This is done so that this collection of words can be arranged structurally and has value. Is a process that consists of Tokenizing, Slang removal, Stop Word Removal, and Stemming. Tokenizing tries to get a collection of words that do not contain punctuation. Furthermore, slang removal is the replacement of slang to standard words. The Stop Word Removal process tries to eliminate words that do not have important meaning such as conjunctions. The last process is stemming. This process seeks to change basic form words.

3. Feature Extraction

At this stage trying to produce features or attributes that have value from a collection of clean words. In other words, this stage is trying to do the structuring of the existing clean data. This collection of clean words is then arranged in the form of Bag of Word (BOW). The BOW form involves the TF-IDF weighting shown in equations 4 and 5. Tf is the frequency of occurrence of the word j in one document while df is the number of documents containing the word j. Then N is the total number of documents. The results obtained at this stage are training data that is ready for training data using a classifier.

$$tf\ idf = tf(j).idf(j) \tag{4}$$

$$idf(j) = log\left(\frac{N}{df(j)}\right) \tag{5}$$

4. Training Data

This stage seeks to conduct data training to get a model. Data training is carried out with the Classifier of Machine Learning. The classifier performed here uses SVM, Decision Tree, Naive Bayes, and Logistic Regression. The model obtained from this training data is used to classify the tweet data that has not been labeled. The training data is no longer used after the model is obtained.

5. Testing Data

This stage attempts to classify tweets (Test Data) that do not have a label. This Tweet will be labeled so that it has positive, negative or neutral polarity. This data testing involves the model and classifier to be able to do the classification. The classifier used must also be in accordance with the type of classifier when conducting data training to produce a model.

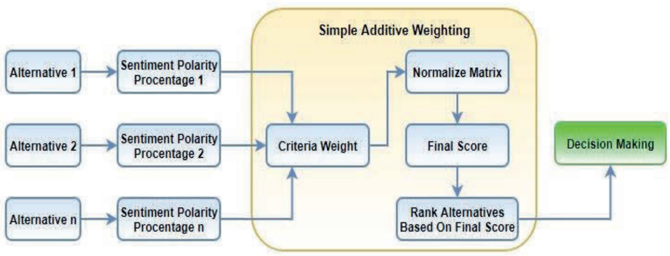

Fig. 4. Generating Alternatives Decision Using SAW

In Fig. 4, there is the final score calculation process using SAW. This calculation starts with the sentiment polarity percentage input from each tweet obtained from SAE. This percentage value is used as a criterion and the criteria weight is calculated. Next, a calculation is made for the Normalization Matrix for positive and negative criteria. Multiplication of the weighting and normalization of this matrix results in a final score for each alternative decision. All alternative decisions are sorted by final score.

VI. RESULT AND DISCUSSION

In this study a proposed framework is produced in Fig. 2. This framework is used for case study of entry-level smartphone selection. This smartphone specification data is taken from the site gsmarena.com. The details of the smartphone data specifications to be selected are shown in Table I.

TABLE I. DAFTAR SMARPHONE

Code	Name	Storage/ RAM (GB)	Camera (Mp)	Price ($)	Battery (mAh)
A1	Realme Narzo 10 A	32/3	12	199	5.000
A2	Xiaomi Redmi 9A	32/3	13	145	5.000
A3	Samsung Galaxy A20	32/3	13	125	4.000

In this case study the decision maker is a potential smartphone buyer. Prospective buyers want to buy one of the 3 types of smartphones in Table I. So, the three types of smartphones are alternative decisions that will be chosen by decision makers. The initial step in accordance with the framework proposed in Fig.2 is to search for tweets with keywords according to the name of the smartphone, the Realzo Narzo 10 A, Xiaomi Redmi 9A, and Samsung Galaxy A20. The search results resulted in the number of tweets for each type of smartphone that is 20 pieces because in SAE it has been set for each keyword to produce a minimum of 20 tweets. The cumulative amount of the tweet is shown in Table II. The number of positive, negative and neutral tweets is used as a criterion value to be calculated by the SAW method.

TABLE II. CUMMULATIVE OF POLARITY TWEETS

Code	Name	Positive (C1)	Negative (C2)	Neutral (C3)	Total
A1	Realme Narzo 10 A	10	4	6	20
A2	Xiaomi Redmi 9A	12	5	3	20
A3	Samsung Galaxy A20	11	4	5	20

Then, the decision maker gives weight to all three criteria, namely C1 = 0.5; C2 = 0.2; C3 = 0.3 so that the total weight is 1 according to equation 3. The biggest criterion is in positive sentiment because this type of polarity most influences the decision taken. In C1 criteria (positive sentiment) is a benefit so that the normalization value of positive criteria is sought by calculating as follows:

$\max(10;12;11) = 12$

$A1 = 10:12 = 0.83$

$A2 = 12:12 = 1$

$A3 = 11:12 = 0.96$

In criterion C2 (negative sentiment) is cost so we look for the normalization value of negative criteria with the following calculation:

$\min(4;5;4) = 4$

$A1 = 4:4 = 1$

$A2 = 4:5 = 0.8$

$A3 = 4:4 = 1$

In the C3 (neutral sentiment) criterion is a benefit so a neutral criteria normalization value is searched with the following calculation:

$\max(6;3;5) = 6$

$A1 = 6:6 = 1$

$A2 = 3:6 = 0.5$

$A3 = 5:6 = 0.83$

Finally, each criterion has a normalized value so that it can be calculated to calculate the final score as follows:

$A1 = (0.5 \times 0.83) + (0.2 \times 1) + (0.3 \times 1) = 0.915$

$A2 = (0.5 \times 1) + (0.2 \times 0.8) + (0.3 \times 0.5) = 0.81$

$A3 = (0.5 \times 0.96) + (0.2 \times 1) + (0.3 \times 0.83) = 0.929$

Final Score calculation results are shown in Table III. In Table III, the alternative order of decisions is in accordance with the largest value of the final score, then the order is A3, A1, A2. So, based on the final score obtained, the biggest alternative decision value is on the A3, the Samsung Galaxy A20. Therefore, the decision maker or prospective buyer should choose the Samsung Galaxy A20 to be purchased based on the calculation of criteria weights which are carried out using the SAW method.

TABLE III. CALCULATION OF FINAL SCORE

Code	Name	Positive (C1)	Negative (C2)	Neutral (C3)	Final Score
Weight	$\sum w_{gij} = 1$	0.5	0.2	0.3	
A1	Realme Narzo 10 A	0.83	1	1	0.915
A2	Xiaomi Redmi 9A	1	0.8	0.5	0.81
A3	Samsung Galaxy A20	0.96	1	0.83	0.929

VII. CONCLUSION

The proposed framework in Fig. 2 contains 4 main stages, namely Crawling Tweets, Sentiment Analysis Engine (SAE), Decision Support System (DSS), and Decision Making. The framework can produce alternative decisions from the sentiment analysis that is built. So, the decision maker does not need to enter the criteria value into the SAW. Criteria values can be generated from the cumulative number of sentiments that are the result of SAE analysis. Therefore, the results of the analysis can be calculated into the final score of alternative decisions using SAW.

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