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MAPPING ACCEPTANCE OF INDONESIAN ORGANIC FOOD CONSUMPTION UNDER COVID-19 PANDEMIC USING SENTIMENT ANALYSIS OF TWITTER DATASET

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ABSTRACT

Computational intelligence based technique becomes popular lately for many application including revealing trend in healthy food consumption. Healthy alternative food that insures the basic physical needs of mankind becomes more popular among people worldwide nowadays. Organic food is believed as alternative food providing sustainable benefit for mankind especially under the pandemic situation that body urgently needs to maintain optimal immune system. Organic food helps to supply sufficient nutrients that is important for body to cope with virus infection. Previously, many studies have been conducted worldwide to exhibit organic foods consumption pattern. The approach can be categorized into two types. The first approach relies on pencil survey and focus group discussion involving a certain number of respondents. The analysis commonly applies statistical techniques. This approach has been considered time consuming and costly. A more sophisticated and time saving technique commonly make use social media platform as the primary tool for revealing the pattern. This study is an initial study to provide model of Indonesian organic food consumer considering that Indonesia is potential for both producer and consumer of organic food. The analysis is based on Twitter dataset and applying computational based technique using Lexicon Based Sentiment Analysis using VADER. Beforehand, we perform text analysis using Force Atlas2 to reveal spatial representation of both attraction force and repulsion force of words. To extent VADER, we employ Indonesian sentiment lexicon namely INSET. The sentiment analysis result confirms that 64% user accept positively organic food as healthy dietary food highlighting the importance of organic food for people to maintain optimal immune system in Covid-19 Pandemic Circumstances. Most of the user that positively post organic food, associate the food with "kesehatan", "praktis", and "diet". Meanwhile, the rest post negatively and regard organic food as having expensive price compared with another kind of food.

Keywords: *Sentiment Analysis, Text Mining, Lexicon-Based, Organic Food, Covid-19 Pandemic, Twitter*

1. INTRODUCTION

People worldwide have exhibited an increasing trend to seek an alternative food, i.e. a high quality food that insures the basic physical needs of mankind. The idea has been shaped by a combination of various aspects concerning food safety, environmental issues, personal needs, local communities and other ethical aspects [1]. In recent years, the production of organic food tends to increase dramatically since it is believed to be an alternative that allow both people and environment gain a sustainable benefit [2]. Organic food is food produced by employing agro-ecological principles in all step of the production process. The principles include the responsibility in using soil, air, water, and the other natural resources while appreciating both local and cultural relation. The term "organic" represents the manners the agricultural products are grown, stored and processed without the use of bioengineered genes, synthetic pesticides and sludge-based fertilizers in maintaining sustainable agricultural system [3]. Many works indicate that organic food contains richer nutrients e.g. omega-3 fatty acids and antioxidants. At the same time, it is GMO-free, fresher and better for environment.

Along with the concern to environmental issues, studying organic food consumption trends among people becomes important [4], not only it is considered to be healthier and more eco-friendly for consumer's dietary choices compared to traditionally grown food [5], but also it concerns to ethical behavior of human values dealing with environment [6]. Accordingly, several recent studies have been conducted worldwide depicting people's behavior in ethical consumption of organic food [7]. In early 2013, a survey has been administered to evaluate

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both Dominica's willingness and ability to pay for organic food [8]. To allow participants from various literacy rates, the face to face interview took place at nine locations of varying population densities, including rural centers and primary market regions. Overall, the study confirmed that Dominicans consumers were willing to pay to pay a 17.5% for organic food. Since cross national study signified different motive for different cultures in purchasing organic food, a study [9] has been conducted to reveal food market in Thailand. The study has reported that mistrust in decision making impact negatively on organic buying behavior. A web based random sampling survey has been employed to examine people's attitude toward organic food in Norway. From 939 respondents that completed the query, only 6% of them that purchased organic food regularly claiming that expensiveness as the major reason for not purchasing. More than 50% of participants underlined the importance of promotion compared with inexpensive price. Four focus group discussions involving 43 participants have been arranged to provide insight toward consumers' attitude regarding organic food of African-American shoppers [10]. The group discussions included two groups of organic food shoppers and the rest was conventional food shoppers. As expected, participants from organic food shopper were more knowledgeable about organic food compared with conventional food shoppers. Surprisingly, organic food shoppers were more accepting of organic label compared with the conventional food shoppers. The same technique using focus group discussion has been employed to reveal consumer perception toward organic food in Germany.

Previous paragraph has emphasized several studies employing both conventional paper survey and focus group discussion to reveal consumers' attitude of organic food in several cultures. Nowadays, along with the development of Web 2.1 platform and the exponential growth of social media content, the most recent studies have changed the approach by adopting the sophistication of social media analysis technique. Several limited most recent studies relied on so called "Sentiment Analysis" technique, a computational approach to extract user's opinion in a social media context.

As one of the most recent topic under Natural Language Processing, Sentiment Analysis which is also known as Opinion Mining can be defined as a computational based technique to extract people's opinion from various kind of data including text data grabbed from social media platform. Sentiment Analysis categorizes positive, negative and neutral opinion of text data grabbed from social media dataset [11].

Since pencil survey was regarded to be time consuming and costly, the new approach has been reliable nowadays [12]. Among the limited studies, Pilar et al [1] employed "organic food" hashtag to grab text data from Instagram between July 4, 2016 and April 17, 2017 worldwide. Statistical and cluster analysis using Gephi 0.8.2 has also been conducted to portray the trend. Users mostly related their experience using organic food with "healthy", "clean food" and "vegan". Another study made use Twitter as a useful tool for Word-of-Mouth communication. The aim of the study is to compare trend of organic food consumption in both Korea and Mexico [13]. The data collection involved Google Search as a popular search engine in Mexico and Naver as a popular search engine in Korea [14]. The semantic network analysis [15] indicated that Mexico was formerly organic food producer, meanwhile, Korea was consumer of organic food. The study has also emphasized the cities in both country having the richest organic agriculture.

Among the previous works concerning organic food, there are limited studies revealing the pattern of Indonesian consumer behavior toward organic food. Indonesia, as a country with high density of population reaching 273 million in 2020 and 38% of them worked in the agricultural sector make it potential to be both consumer and producer of organic products [16]. Moreover, the growth of population was accompanied by the growth of socio-economically middle class depicting the growing prosperity among community. This middle class has relatively high awareness toward healthy consumption indicating the potential acceptance toward organic products. Furthermore, under the situation of the spread of Covid-19 Pandemic in Indonesia nowadays as part of ongoing worldwide Covid-19 pandemic, the issue of healthy food becomes urgent among people. Healthy food as of organic food is crucial to ensure good supply of sufficient micronutrients and macronutrients for the body. The sufficient nutrients help the body to maintain optimal immune system that in turn will keep the body against internal and external insults including Covid-19 infections [17].

Among the studies that have been conducted to capture market trend of organic food in Indonesia are the work of [18], [19] and [20]. The first work made use pencil survey of 200 respondents recruited from middle-class shopping mall. The study indicated that organic food products were familiar among upper middle class.

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However, only 13% of them have been purchasing the product ordinarily. This work [19] chose Focus Group Discussion of 218 respondents to reveal the motive for consuming organic food products. Confirmatory Factor Analysis indicated several external factors influencing purchase decision i.e. life partner, family, and friends. Meanwhile, [20] modelling customer perception of organic food consumer using 100 respondents. The employed analysis technique is multi attribute attitude model. All of the studies captured the condition before pandemic and employed pencil survey based approach.

The best we know this study is an initial effort to model the organic food consumption of Indonesian consumer using social media analysis technique. The aim of this study is to provide more recent, yet time saving analysis about the purchase decision pattern of Indonesian consumer especially under Covid-19 Pandemic situation. Referring to the previously highlighted key reference as background studies, the motivation of this work comprised:

1. Providing an efficient technique based on text intelligence to reveal acceptance model of Indonesian organic food consumption
2. Applying a sentiment analysis algorithm to extract acceptance model of Indonesian organic food consumption

The data source is collected by grabbing social media information based on geo-located information. The approach is also considered to be appropriate under the pandemic situation. As of 28 May Indonesia reached the second highest in Southeast Asia, after Singapore in term of positive cases. Indonesian government has authorized large-scale social restrictions, a lockdown-like policy. In this situation, pencil survey-based approach is not a suitable choice to be conducted. The exponential growth of social media data has also made it as a rich source of information [21]. A survey conducted in 2017 indicated that over 143 million of Indonesian is active internet users. Among the users, Twitter is the most popular social media platform for sharing information. Compare with the other platforms, Twitter presents more compact yet valuable information allowing it to be more reliable as source tool for pattern analysis [22]. Although different method and approach has been employed [15], mostly confirmed that the result of Twitter data analysis was convincing [23]. Accordingly, this work use Twitter as the source of information to generate analysis of Indonesian organic food consumer behavior especially under the pandemic circumstance.

2. RELATED WORK

Sentiment Analysis (SA) is a recent research topics involving text analysis and computational linguistics [21]. In term of text analysis [15], Sentiment Analysis is a computational based study to extract affective feature of a piece of text data. It make use of natural language processing approach to calculate overall sentiment score of a given text data [24]. With the exponential growth of electronic Word of Mouth (eWOM), Sentiment Analysis becomes prominent method to process the subjective information.

Two major techniques commonly employed for SA tasks involve lexicon based technique and machine learning based technique. In revealing sentiment of a text data, lexicon based technique count on a predefined dictionary containing collection of sentiment term called sentiment lexicon such as NRC emotion lexicon [25], SenticNet [26], Harvard General Inquirer, MPQA subjectivity lexicon [27], SO-CAL [28], and Bing Liu's Opinion Lexicon. Lexicon based technique firstly extract part of speech (POS) of a sentence to take sentiment term commonly having POS of verb and adjective. Employing sentiment lexicon, the technique then populates sentiment orientation of a document. Another popular technique involves machine learning application. In this kind of approach, SA is regarded as an ordinary text classification task. The technique classifies a piece of text into one out of three categories i.e. positive, negative, and neutral. In the first step, the employed method building models using a set of training data. Lastly, the machine learning assign the class of the data based on the predefined model.

SA holds an important role since it has a wide range of application. The exponential growth of online platform has also driven the use of SA in extracting subjective information within the online text data. Budiharto made use Twitter dataset to predict Indonesian Presidential Election 2018 results. Relevant hashtags such as #Pilpres 2019, #Pemilu 2019, #Noblackcampaign, #Indonesiabisa #NKRI, #Indonesiahebat was crawled using Twitter API from March to July 2018. The work proposed a framework to count important data and top word as well as to train the model of Machine Learning Algorithm. The authentication was performed using OAuth Package of R language [22]. The result confirmed that Jokowi lead the prediction. The result corresponded with the results of four survey institutes.

The same technique has been employed to predict the result of USA presidential election in 2016 [29]. The data was gathered from three state i.e.: Florida, Ohio and North Carolina using Streaming API involving several hashtags i.e.: #donaltrump, #hillaryclinton, #maga, #imwhitter, #nevertrump and #neverhillary. A supervised sentiment analysis technique using Naïve Bayes was used to build the training model of algorithm and the prediction was then proven to be accurate.

SA have also helped modeling people's perspective toward an emerging technology in i.e. perovskite solar cell technology. In the study [30], SA and data mining on Twitter dataset have been used to identify people's topic of interest over time to track the development trend of perovskite solar cell technology. The proposed framework compared technical information attached in patents with Twitter user's response to, sense of, and the outlook for the emergint technology. SA have been proven to contribute in shaping the knowledge of how the technology emerge and develop.

Indeed, SA have been used to investigate people's response to terrorist attack [31]. Using Twitter API, the data was collected based on several hashtags i.e.: #berlinassassination,#breitscheidplatz, #wearebrlin, #prayforberlin, #anschlagberlin, #berlinattack, #berlinattacks, #prayforgermany #Iamaberliner, #wirsindberlin #berlinattentat, #ichbineinberliner, and #bestrongforberlin. Complemented with terror management theory (TMT), structural topic modelling with SA have been used to understand public's sense making perspective toward 2016 terrorist attack on the Berlin Christmas market. The study has found that Twitter was capable to serve as suitable platform for finding, sharing information, and establishing a standard.

SA has also been used to extract people's attitude toward product within product review dataset [12]. In this work, the study attempted to the performance of supervised SA task on product reviews by introducing semantic features of text data extracted using Word Sense Disambiguation method to handle polysemy of words. The proposed method was validated using several Machine Learning Algorithms i.e.: Naïve Bayes (NB), Naïve Bayes Multinomial (NBM), Logistic (LOG), Simple Logistic (SL), Decision Tree (DT), Radial Function (RF) and Feature Selection Methods i.e.: Correlation Feature Selection (CFS), Information Gain (IG), Principal Component Analysis (PCA), and compared with two baseline Bag of Words features i.e.: 1) Unigram and Bigram [32]. The experiment confirmed that the proposed features outperformed the two baselines.

Similarly, another study [11] proposed Sentence Level Features and Domain Sensitive Features of product review to enhance supervised SA task on product reviews. The authors argued that semantic of word in sentence level was importance [33] since the same words that emerge in difference text pieces might shares different senses. Moreover, Senticircle [34] suggest that words emerges in the same context tend to share the same senses. Extracted using both adapted WSD [15] and Senticircle method, the features outperformed BoW features in several performance metrics i.e.: 1) precision, 2) recall, 3) f-measure and 4) accuracy. Making used of WEKA Machine Learning Platform [35] and validated using Amazon Product Data, the proposed method was important milestone for developing new text features.

In another study [21], a lexicon based technique was introduced to reveal people's attitude toward a product within a product review dataset. Firstly, local context was defined from a word sense disambiguation method. Next, global context was also incorporated to address contextual issue of word correspond with its specific domain of product review. Validated using several Amazon Product Data, the novel proposed lexicon based sentiment analysis method outperformed several baselines in term of precision, recall, f-measure and accuracy.

3. METHOD

The mapping process of the acceptance can be presented as a framework and include several steps as presented in Fig. 1. The steps include grabbing dataset from Twitter using Twitter API, Hashtag Clustering using Gephi, data collection into Database, Text Preprocessing, Sentiment Analysis task, and generating acceptance map based on Twitter Dataset. In this work, we regard Indonesian Twitter user as the sample/ respondents of the research so that we assume that their comments represent people's attitude toward organic food consumption.

In the first step, we grab Tweets from Twitter using Twitter API. We employ OAuth package of R language to authenticate link of Twitter API with Twitter account [23]. Firstly, we grab tweets with hashtag #makananorganik. We then generate word network using ForceAtlas2. ForceAtlas2 simulates spatial representation of the network where node repulse each other and edge attract the nodes [24].

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ForceAtlas make possible to reveal both attraction force F_a and repulsion force F_r. Both forces are key features in network spatialization. Attraction force indicates linear distance $d(n_1, n_2)$ between two nodes n_1 and n_2 as presented in formula (1). The force is proportional to the distance between nodes $d(n_1, n_2)$.

$$F_a(n_1, n_2) = d(n_1, n_2) \quad (1)$$

Jacomy [36] formulated repulsion force to indicate poorly connected nodes to very connected nodes as presented in formula (2) where deg indicates degree of the nodes n.

The repulsion force is reciprocal to to $(deg + 1)$ of two nodes ensuring that even the node with zero degree will still possess repulsion force. The formula was similar to one proposed by Noack [37].

$$F_r = kr\ \left((\deg(n_1) + 1)(\deg(n_2) + 1)\right)/(d(n_1, n_2))$$

(2)

Firstly, we conduct text pre-processing task as a common step in text mining methods. The task incorporates: 1) Case Folding, 2) Tokenizing, 3) Filtering (Stop Word Removal), and 4) Stemming. Yet, in this work we do not handle slang word. Handling slang word need to employ a slang word library. All of the pre-processing task was carried out using Python Sastrawi. The stem of Python Sastrawi was originated from Kateglo library.

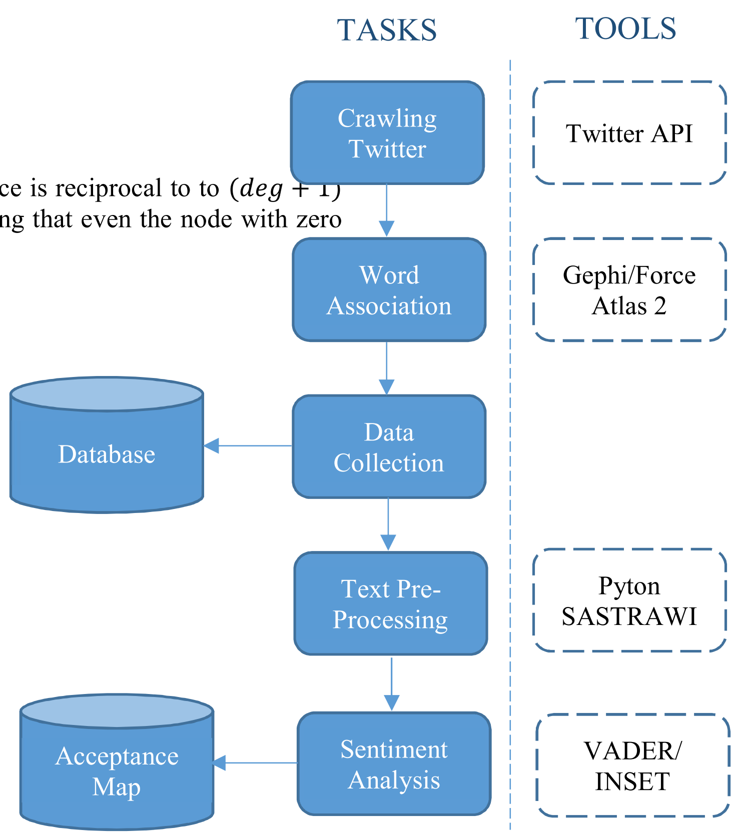

Figure 1: Framework of the Method

We then conduct Sentiment Analysis task to interpret user experience toward organic food in Pandemic circumstance. There are two techniques commonly employed for Sentiment Analysis tasks i.e. 1) Machine Learning Based approach and 2) Lexicon Based approach. Machine learning based approach is supervised sentiment analysis technique that relies on Machine Learning algorithms. Meanwhile, Lexicon Based approach depends on a pre-annotated sentiment lexicon.

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In this work, we make use PHP Sentiment Analyzer package that employ VADER (Valence Aware Dictionary and Sentiment Reasoner) [38]. Unlike another sentiment lexicon, VADER is a valence-based sentiment lexicon that takes into account the intensity of sentiment of words as opposed to only polarity of words.

Algorithm 1: Code to assign Sentiment Orientation of Twit

```
$url = "https://api.twitter.com/1.1/search/tweets.json";
                    if($search != "")
                    $search = $search;
                    $query = array( 'count' => 100, 'lang'=>'in', 'geocode'=>$lokasi, 'q'
=>urlencode($search), "result_type" => "recent");
                    $oauth_access_token = "1859799367-
TtqNKuLdewRKuJmdFBS1BKuO9B9WMcs9SBnS3aa";
                    $oauth_access_token_secret =
"sj77ZcNXgawck1YxDzme8OEHQckFc6dv2YXYKCMGSm03Q";
                    $consumer_key = "DvdQxfxpZx4Km8ovk8Grn02US";
                    $consumer_secret =
"dOBcgfMRffZwGfTJepvk42Bn6Je2l4nFSBABVVNgNT4uy70OLk";
                    $oauth = array(
                              'oauth_consumer_key' => $consumer_key,
                              'oauth_nonce' => time(),
                              'oauth_signature_method' => 'HMAC-SHA1',
                              'oauth_token' => $oauth_access_token,
                              'oauth_timestamp' => time(),
                              'oauth_version' => '1.0');
                    $base_params = empty($query) ? $oauth : array_merge($query,$oauth);
                    $base_info = $this->buildBaseString($url, 'GET', $base_params);
                    $url = empty($query) ? $url : $url . "?" . http_build_query($query);

                    $composite_key = rawurlencode($consumer_secret) . '&' .
rawurlencode($oauth_access_token_secret);
                    $oauth_signature = base64_encode(hash_hmac('sha1', $base_info, $composite_key,
true));
                    $oauth['oauth_signature'] = $oauth_signature;

                    $header = array($this->buildAuthorizationHeader($oauth), 'Expect:');
                    $options = array( CURLOPT_HTTPHEADER => $header,
                              CURLOPT_HEADER => false,
                              CURLOPT_URL => $url,
                              CURLOPT_RETURNTRANSFER => true,
                              CURLOPT_SSL_VERIFYPEER => false);
                    $feed = curl_init();
                    curl_setopt_array($feed, $options);
                    $json = curl_exec($feed);
                    curl_close($feed);
                    return  json_decode($json);
```

Accordingly, VADER assigns three sentiment scores to a words i.e. positive score, negative scores and neutral scores. To apply VADER [38] for Indonesian language, we need to insert collection of Indonesian positive and negative words to the package. For that reason, we utilize Inset Lexicon [39] containing 3609 positive words and 6609 negative words of Indonesian language. To assign sentiment orientation of a Twit, we employ script as shown in Algorithm 1.

In short, the research setup will be conducted by following these steps of framework:

1. Grabbing Twitter data from Twitter using Twitter API,
2. Generating word cloud as well as word association using Gephi.
3. Performing Text Pre-processing using Python Sastrawi.
4. Mapping Indonesian organic food consumer acceptance using Sentiment Analysis technique employing VADER from the grabbed Twit.
5. Highlighting finding from the employed Sentiment Analysis technique.

4. RESULT AND DISCUSSION

From the grabbed twit, we generate word cloud as seen in Figure 1 to visualize words that extensively related with #Makanan Organik. The size of the text in word cloud simply indicates frequency of appearance of the words in Twits but not directly describes the association of the word with #Makanan Organik.

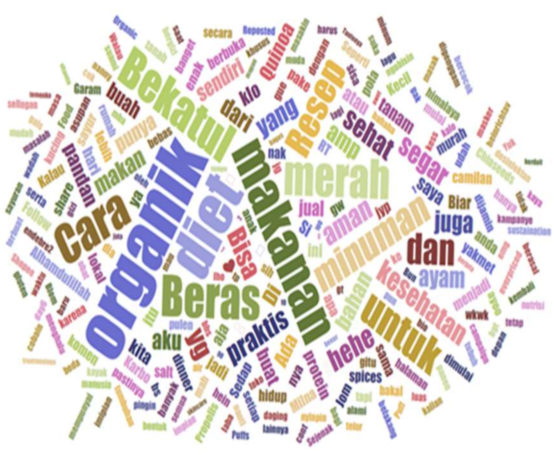

Figure 2: Word Cloud of #Makanan Organik

To investigate the association of the words with #Makanan Organik, we generate word network using ForceAtlas2 of SocioViz. We present the 5 most frequent words in Table 1 along with its sentiment orientation. The table indicates that twitter user mostly associate #Makanan Organik with positive impression. Yet, user considers #Makanan Organik costs quite expensive compared with another common food. This result validates the work of [18] emphasizing that #Makanan Organik is quite costly.

Table 1: The 5 most frequent word associated with #Makanan Organik

Associated Word	Sentiment
Kesehatan	Positive
Praktis	Positive
Diet	Positive
Makanan	Neutral
Mahal	Negative

To assign sentiment orientation of a twit O_t, we employ Rule (3).

$$O_t = \begin{cases} positive\ if\ |T_{pos}| > |T_{neg}| \\ negative\ if\ |T_{neg}| > |T_{pos}| \\ neutral\ if\ |T_{pos}| = |T_{neg}| \end{cases} \quad (3)$$

Where the value of T_{pos} and T_{neu} are calculated using formula (4) and formula (5) as follows:

$$T_{pos} = \sum_{i=1}^{n} tpos_i \quad (4)$$

$$T_{neg} = \sum_{i=1}^{n} tneg_i \quad (5)$$

In formula (4) and (5), $tpos_i$ and $tneg_i$ are positive value and negative value of word picked from VADER. Meanwhile, n is the number of token of a twit after being assigned with a complete text pre-processing. We ignore the neutral value of the word in VADER library. From the grabbed twit, 64% positively accept organic food as presented in Fig 3. The result highlight the importance of organic food as a healthy dietary food especially under Pandemic situation. Most of the user that positively post organic food, associate the food with “kesehatan”, “praktis”, and “diet”.

Meanwhile, the rest post negatively and regard organic food as having expensive price compared with another kind of food. The number of post regarding with the topics is presented in Figure 4.

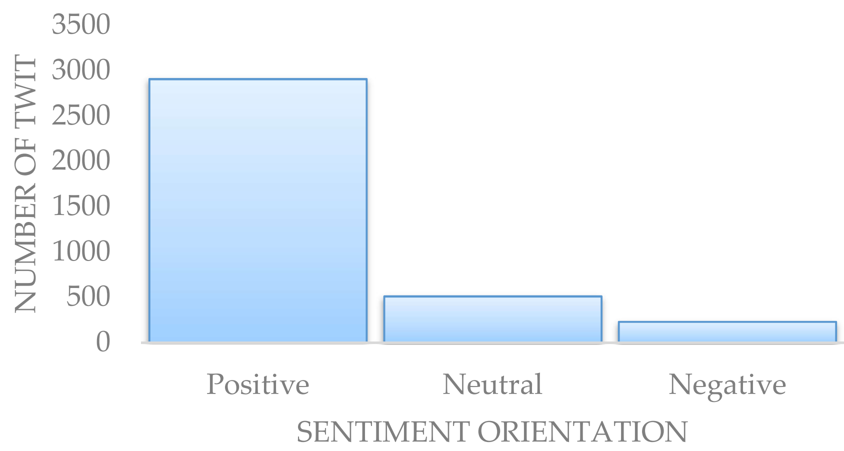

Figure 3: The result of Sentiment Analysis Using VADER

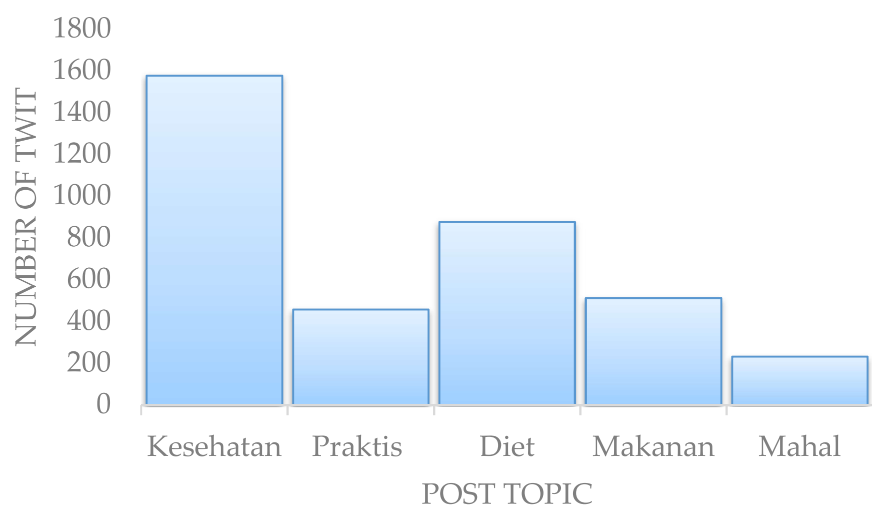

Figure 4: Number of Post according to its Topic

5. CONTRIBUTION AND ORIGINALITY

There are two type of techniques employed for modeling consumer acceptance toward organic food consumption. The common technique adopted by previous work to reveal Indonesian consumer acceptance toward organic food consumption [18], [19], [20] relies on a pencil survey that analyze the result of respondent's answer to a set of questionnaire. The pencil survey based technique is regarded to be time consuming, costly and sometimes containing bias. In this work, we utilize a more sophisticated method based on Sentiment Analysis of text dataset grabbed from Indonesian Twitter user. This work is capable of revealing the comparable result as pencil survey technique yet in a timesaving and less expensive manner.

6. CONCLUSION

Compared with common technique to generate acceptance model of Indonesian organic food consumption that apply pencil survey technique, this work employ a computational intelligence based method that is less expensive yet timesaving with a comparable result. The technique adopts Sentiment Analysis of Twitter Dataset. The technique includes generating word association using Force Atlas2 and sentiment analysis using extended VADER library. Most of the user that positively post organic food, associate the food with “kesehatan”, “praktis”, and “diet”. Meanwhile, the rest post negatively and

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regard organic food as having expensive price compared with another kind of food. From the grabbed twit, the study also highlights that 64% of twitter user positively accept organic food as their healty daily diet.

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