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Sentiment Analysis to Identify Public Opinion for *Zakat* Implementation in Indonesia Using Machine Learning Algorithms

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Abstract: This research aims to explore and identify public opinion related to *Zakat* in Indonesia by utilizing big data technology through sentiment analysis. The source of Twitter's social media public opinion data is used in the research. Proper keywords need to be determined before crawling Twitter data collections. The Twitter data collected in the research was 1060 Twit at the beginning of the year 2020. Indonesian community opinion identification, a part of the machine learning method, was a method used in training and testing data requirements. Opinions are classified into 3 classes i.e. positive, neutral and negative. The identification shows that the Random Forest Classifier method and the Naïve Bayes method provide an accuracy value of 86% and 81%. While the method that produces the lowest accuracy is the Support Vector Machine method of 53%. The accuracy results show that the sentiment of analysis can be used as an "early warning system" for the decision-makers of *Zakat* in Indonesia.

Keywords: Machine Learning, Opinion, Sentiment Analysis, Twitter, *Zakat*

1. Introduction

This study aims to model the analysis of public opinion related to the management of *zakat* by *zakat* institutions in Indonesia in the form of sentiment analysis. *Zakat*, seen from the perspective of economics, has a positive correlation with consumption figures that will drive the economy. The macro consumption model is determined by basic consumption and consumption that comes from income. If seen from the mustahik side, then *zakat* will increase the aggregate of basic consumption, namely the accumulation of basic consumption (Aziz, 2014).

Management and distribution of *zakat* is a concern for *zakat* managers in Indonesia (Parisi, 2017). Good *zakat* management will have an impact on people's welfare (Aziz, 2014). The standardization of *zakat* management in Indonesia is managed by the government *zakat* institution, the National *Zakat* Board (BAZNAS). The potential and realization of *zakat* receipts in Indonesia increased during the 2011-2015 period. However, there is a very large gap between the potential value and the amount of realization. During 2011-2015 the realization of *zakat* receipts was less than 1%. One possibility is that the majority of Indonesians prefer to distribute their *zakat* directly to *muzakki*, so it is not recorded (Canggih et al., 2017). There are increasing problems at Indonesian *Zakat* Institutions (IZI), namely socialization costs, the number of volunteers, the amount of *zakat* collected, and the distribution of consumptive *zakat*, which cumulatively reduces the intermediation function of *zakat* institutions. IZI must resolve this problem to improve the efficiency of the *zakat* institution (Al-Ayubi et al., 2018).

Zakat institutions are institutions that are responsible for managing the collection and distribution of *zakat* funds. The Qur'an explains the appointment of officials to collect and distribute *zakat*, which must be in the form of state departments or public funds that are fully managed by public bodies (Alonso, 2015). *Zakat* has become an important source of funds for the development of Islam since the entry of Islam in Indonesia. During the Dutch colonial period, the Colonial Government-issued Bijblad Number 1892 on August 4, 1893, which contained the Colonial Government's policy regarding *zakat*. The purpose of the issuance of this regulation is to prevent the occurrence of *zakat* financial misappropriation. The naib worked to carry out the administration of the power of the Dutch Colonial Government without getting a salary to finance their lives (Muhammad Aziz, 2014).

According to We are Social data, there are 175.4 million internet users in Indonesia in early 2020. Compared to the previous year, there was an increase of 17% or 25 million users. The data shows that 64% of Indonesia's population is connected to the internet and social media. The size of the population, the rapid growth of internet and telephone users are potential for the national digital economy. One source of data on big data is social media which has high quality and can be directly consumed by the public. Many researchers have given more attention to social media. Data analysis using social media is not easy because of its incompleteness and dynamic nature (Wang et.al., 2014, Santilana et.al., 2015).

2. Related Works

The analysis of social media data that is most widely used to identify public opinion is sentiment analysis. This method is widely used for the prediction or early identification of an organization in capturing the opinions of social media (Mäntylä et.al, 2018, Hui et.al, 2017). Social media attract computer scientists and statisticians as research opportunities because social media provides an impressive amount of data about users and their interactions. The most discussed and interesting thing is predicting future events and developments from social media data (Schoen et.al., 2013, Neethu and Rajasree, 2013).

Sentiment Analysis or Opinion Mining is a way to compare people's emotions, attitudes, and opinions about a particular entity. Entities can represent individuals, events, or topics (Ridzwan Yaakub et.al., 2019, Whitelaw et.al, 2005). The main focus of Opinion Mining is to extract and analyze people's opinions about an entity while sentiment analysis identifies the sentiments expressed in the text and then analyzes them.

Some critical opinions in all involved parties would be categorized into several groups. Opinions from a group who received *zakat* (mustahik), who distribute the *zakat* (*amil*), and who pay the *zakat* (*muzakki*). However, there is a significant percentage of parties that are not in those groups. They don’t either pay or receive the *zakat* and they are also not the distributor. Indeed, based on Islamic guidelines there are very clear requirements for every group. However, in real life, it’s not easy to identify each group as no sufficient data, no law enforcement, relative term definition, and other human being-related characters.

From the mustahik groups, the consumptive patterns and productive patterns would be important issues in utilizing *Zakat* aid. It’s believed mustahik would utilize *zakat* in productive spending and empower them in terms of poverty alleviation (Sumai et al., 2019). It is also supported by (Qamaruddin et al., 2019).

World Bank reported in the last two decades the majority of the poor and vulnerable in Indonesia have uplifted from poverty into the aspiring middle class even though the determinant of those groups tends to measure by ending up in how much money they spend. Based on (BAZNAZ Outlook, 2020) there are approximately 115 million people who belong in the aspiring middle-class category.

On the other hand, based on (BAZNAZ, 2020) the potential total of *Zakat* in Indonesia right now is Rp 233,84 trillion. Furthermore, the reinforcement of *zakat* management through financial technology systems has been studied but it is difficult to find existing work on social media involvement in *Zakat* matters in Indonesia. The realization of BAZNAS fund distribution for the Covid-19 handling program has reached more than Rp 16 billion.

Report dissemination through social media would help in transparency and trust among *Zakat* stakeholders. One of the social media is Twitter and in analyzing comments from Twitter is sentiment analysis. However, sentiment classification will result in sentimental polarities. It is common knowledge that most universe phenomena have been in pairing. In our sentiment analysis, we also put word labelling in two labels i.e. positive and negative but we are also aware of a position in the middle or neutral. Thus, sentiment classification is a central issue in sentiment analysis. Positive could be interpreted as good and negative as bad.

Machine learning creates a model based on regularities found in vast volumes of data, which is then used to generate predictions and categorize raw data. There are a number of different machine learning algorithms which all have different use cases and may result in different accuracy with the same case. This paper applied seven algorithms in machine learning i.e. Support Vector Machine (SVM), Logistics Regression, K-Nearest Neighbor (KNN), Decision Tree, Gaussian Naïve Bayes, Boost Classifier, and Random Forest Classifier.

3. Method

In conducting research, the identification of public opinion related to *zakat* management uses a sentiment analysis approach from Twitter social media. Data on public opinion was obtained from tweets during the March period with a total of 1060 data tweets that have been cleared. The process of crawling twitter data in this study is illustrated in Figure 1. Before performing the data crawling process, first, identify the source of the research object, reference sources are obtained from several journals and books related to *zakat*, sentiment analysis, and machine learning. All available sources are used to determine the right keywords at the time of crawling the data.

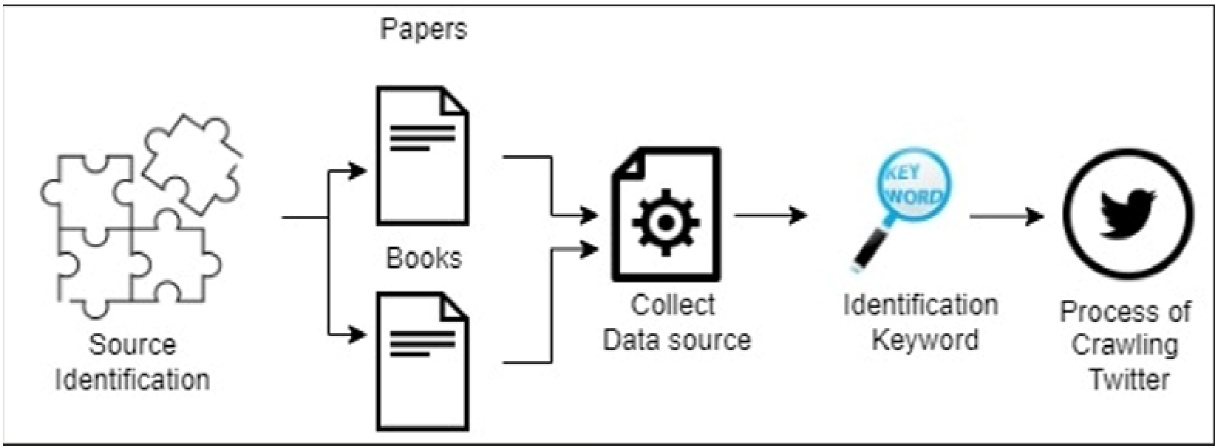

Figure 1: Block Diagram of Crawling Process

The stages of the research carried out are shown in Figure 2. The first step taken is to define data requirements. The data used is social media data on Twitter, so it needs to determine the right keywords in crawling data. The main objective of this study is to obtain input from the public on the management of *zakat* in Indonesia by the National Alms Board (BAZNAS). The second step in the form of data collection in the form of text from Twitter was taken in the period March 2020 because this month the government began implementing the period of large-scale social restrictions (PSBB) and the community began to be affected by the economic downturn and how BAZNAS assisted the community with the impact of Covid-19 on the people's economy. After the data collection is done the data cleaning aims to clean the tweet data so that the text data will be easily processed. Data cleaning steps can be seen in Figure 3.

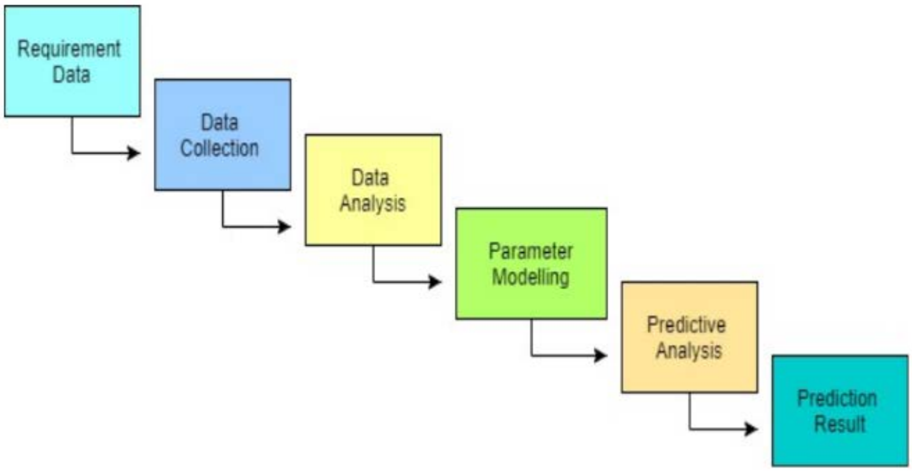

Figure 2: Stages of Research Methodology

The third step is to analyze the data by determining the model for opinion classification in the form of sentiment analysis. The next step is to determine the parameters of the model used to classify. The dataset will be divided into 2 namely training data and testing data. The model parameters used are to conduct training and data testing is used to determine the accuracy of the existing models. The fifth and final step is to test predictions of new opinion data and display prediction results based on the model with the best accuracy.

This study uses 7 machine learning algorithm models to classify the support vector machine (SVM), Logistics Regression, KNN, Decision Tree, Gaussian Naïve Bayes, Boost Classifier, and Random Forest Classifier. The software used for data processing uses the sklearn library in Python that is run using Jupyter.

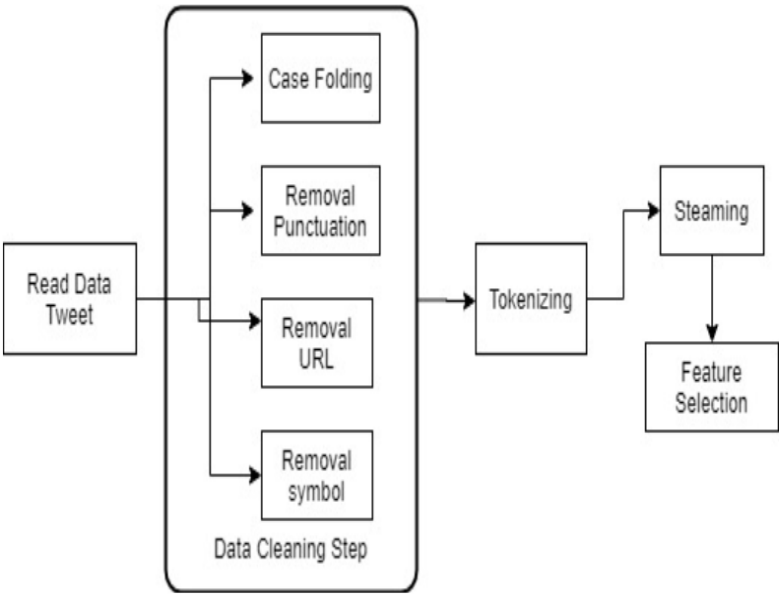

Figure 3: Data Cleaning Process

The data cleaning process shown in Figure 3 includes:

a. Case Folding is the first pre-processing step we will take is to turn our tweets into smaller cases.
b. Removing Punctuations because when handling text data, it does not add any additional details. Removing all instances of this would also help us reduce the size of the training results.
c. Removal URL is deleting the URL in the Twitter text
d. Removal Symbol is removing all symbols that have no meaning
e. Tokenization refers to breaking the text into a series of words or phrases.
f. Stemming is the process of changing a word into its root word by removing affixes to words in documents or changing a verb to a noun.

The stages of data cleaning carried out in this study used modules in python. One of the stages of data cleaning tokenization is shown in the coding snippet in Figure 4.

```
# tokenization

df['new_text'] = df["text"].apply(lambda x: x.split())
df.head()
```

	text	label	new_text
0	ada delapan nama yang didukung forum zakat men...	0	[ada, delapan, nama, yang, didukung, forum, za...
1	ada delapan nama yang didukung forum zakat men...	0	[ada, delapan, nama, yang, didukung, forum, za...
2	agam sumatera barat bantuan ziswaf zakat infak...	2	[agam, sumatera, barat, bantuan, ziswaf, zakat...
3	agam sumatera barat bantuan ziswaf zakat infak...	2	[agam, sumatera, barat, bantuan, ziswaf, zakat...
4	ajak asn di tanjab barat bayar zakat melalui b...	0	[ajak, asn, di, tanjab, barat, bayar, zakat, m...

Figure 4: Tokenization in Python

Tokenization is the process of converting a valuable piece of information, such as an account number, into a meaningless string of characters known as a token. Tokens can be used to refer to the original data, but they can't be used to estimate the values.

4. Results and Discussion

In this section, the results and discussion of the research will be displayed. In the research design, it was conveyed that the data used to identify opinions was 1060 tweet data in March 2020. After the data was cleared, the tweet data labelling into 3 sentiment classes were positive, neutral, and negative. From the data of 1060, most of the public opinions related to *zakat* management bodies in Indonesia are neutral. The class grouping histogram data is shown in Figure 5.

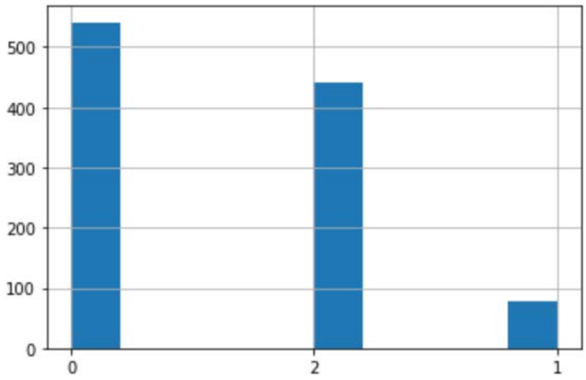

Figure 5: Histogram of Opinion Class

The neutral class has more than 50% that is 500 more tweets, the positive class is almost 450 tweets while the negative opinions are less than 100 tweets. The dataset is used for training as much as 80% and the remainder is for testing models with the best accuracy. The dataset that already has a label will display the distribution of words that often appear based on sentiment class in the form of the word cloud. Word-cloud positive opinion seen in Figure 6, neutral opinion in Figure 7, and negative opinion seen in Figure 8.

Figure 6: Positive Opinion

Figure 7: Neutral Opinion

Word-cloud positive opinion and neutral words that often appear almost the same that is the word "badan" "*amil*" "nasional". Badan refers to an institution that distributes *zakat*. Amil refers to a person who deserves compensation for completing a *zakat* collection. Nasional refers to the national or country level. On the other hand, the appearance is different when it was compared to negative opinion word-cloud, in which the words that often appear are "bayar", "target" and "kemenag". Bayar refers to *zakat* payment, target means target. Kemenag refers to the Ministry that *zakat* matters portfolio.

Figure 8: Negative Opinion

The frequency of occurrence of words from the three opinion groups is displayed in the form of a histogram in Figures 9-11.

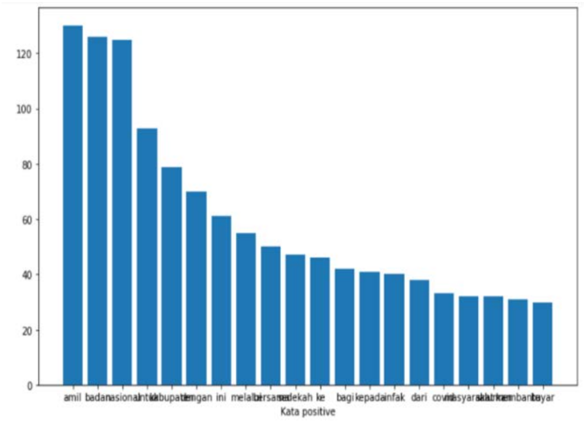

Figure 9: Frequency Positive Opinion

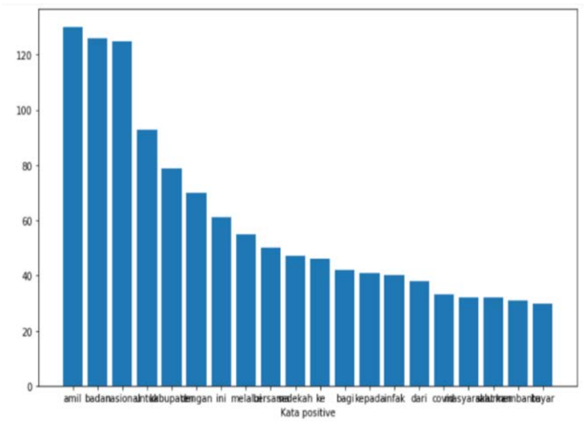

Figure 10: Frequency Neutral Opinion

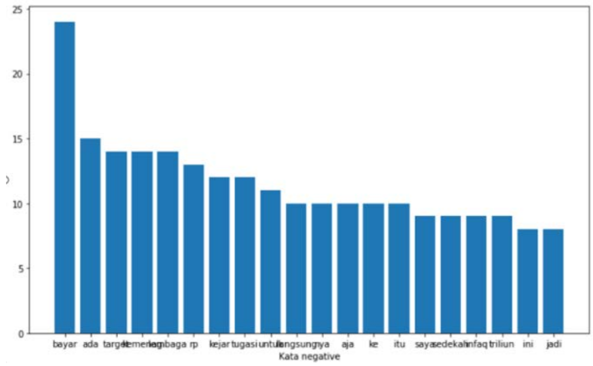

Figure 11: Frequency Negative Opinion

The dataset used in this study is divided into 2, namely for training 80% or 1038 data and for testing 20% or 260 data. The distribution of the dataset for training and testing is shown in Figure 12.

```
X_train, X_test, y_train, y_test = train_test_split(df.new_text, df.label.astype(float),
                                                    test_size=0.2, random_state=42)


print("Text train shape : ", X_train.shape)
print("Label train shape : ", y_train.shape)
print("Text test shape : ", X_test.shape)
print("Label test shape : ", y_test.shape)
```

```
Text train shape :  (1038,)
Label train shape :  (1038,)
Text test shape :  (260,)
Label test shape :  (260,)
```

Figure 12: Dataset of Research

Figures 9 and 10 show that the words of the national *amil* body have almost the same frequency, meaning that the public still sees that one of the national *amil* bodies has a pretty good performance because the number of neutral opinions is still more than positive opinions. While the frequency of words that appear on negative opinions relates to the payment of *zakat* and there are still people who have not fully entrusted the payment of *zakat* to the national *zakat* body. The public also sees a negative thing related to the BAZNAS target in collecting *zakat*.

The model used to test the class identification of public opinion shows varying accuracy from some of the models used. The accuracy of each model is shown in Figure 13 and Table 1.

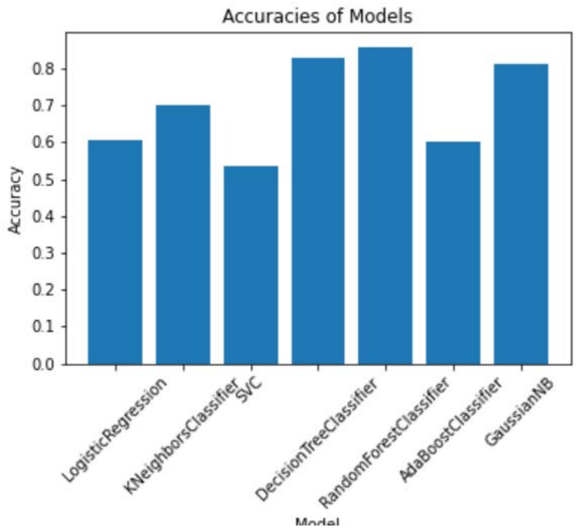

Figure 13: Histogram of Model Accuracy

Table 1: Machine Learning Algorithm Classification Accuracy

Machine Learning Algorithms	Accuracy
Logistic Regression	0,6069
KNeighbors Classifier	0,7013
SVM	0,5346
Decision Tree	0,8270
Random Forest Classifier	0,8553
AdaBoost Classifier	0,6006
Gaussian	0,8113

The 7 classification models used in this study obtained an accuracy of above 80% are the 86% Random Forest Classifier, 83% Decision Tree Classifier, and 81% Naïve Bayes Classifier. While the model with the smallest accuracy is the Support Vector Machine model of 53%.

5. Conclusion

In this study, the results obtained that the identification of community opinion about the management of *zakat* by the Indonesian BAZNAS by using social media data-based sentiment classification approach can be used as additional knowledge by BAZNAS in decision making. The big data approach used to identify opinions in this study is able to provide an accurate value of 86% for the Random Forest Classifier method, while other methods have an accuracy value below that value. Data on the classification of positive public opinion towards BAZNAS was 42%, more than 50% showed a neutral attitude and less than 10% showed negative opinions, thus, the public has viewed BAZNAS as positive. Twitter sampling as a dataset is strongly influenced by several parameters including the keywords used when crawling data, the retrieval period, and the amount of data taken. This parameter will affect the results of the final identification of public opinion on existing research objects.

6. Acknowledgements

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