Journal of Information Systems and Telecommunication
Vol.11, No.2, April-June 2023, 94-101
http://jist.acecr.org
ISSN 2322-1437 / EISSN:2345-2773

Hoax Identification of Indonesian Tweeters Using Ensemble Classifier

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Received: 21 Jan 2022/ Revised: 04 Jun 2022 / Accepted: 07 Jul 2022

Abstract

Fake information, better known as hoaxes, is often found on social media. Currently, social media is not only used to make friends or socialize with friends online, but some use it to spread hate speech and false information. Hoaxes are very dangerous in social life, especially in countries with large populations and ethnically diverse cultures, such as Indonesia. Although there have been many studies on detecting false information, the accuracy and efficiency still need to be improved. To help prevent the spread of these hoaxes, we built a model to identify false information in Indonesian using an ensemble classifier that combines the n-gram method, term frequency-inverse document frequency, and passive-aggressive classifier method. The evaluation process was carried out using 5000 samples from Twitter social media accounts in this study. The testing process is carried out using four schemes by dividing the dataset into training and test data based on the ratios of 90:10, 80:20, 70:30, and 60:40. The inspection results show that our software can accurately detect hoaxes at 91.8%. We also found an increase in the accuracy and precision of hoax detection testing using the proposed method compared to several previous studies. The results show that our proposed method can be developed and used in detecting hoaxes in Indonesian on various social media platforms.

Keywords: Hoax; Identification; Bahasa Indonesia; N-Gram; TF-IDF; Passive-Aggressive Classifier.

1- Introduction

With the development of technology, all kinds of information can be accessed very easily using various devices connected to the internet. One of the most widely accessed media by the public using the internet is social media initially, social media was created to communicate greetings between friends in cyberspace, but in its development now, social media is used to spread hate speech and fake information or hoax. Data from the Ministry of Communication and Information (KOMINFO) of the Republic of Indonesia shows about 800,000 Hoax Spreading Sites in Indonesia. The Ministry of Communication and Information's preventions include blocking sites that spread hoaxes and conducting socializations about hoax news and its dangers both in print media, television media, online media, and social media. Social media has a positive or negative impact. Among the positive effects is an increase in public literacy regarding certain conditions, cases, or events, for example, Covid-19. From social media, we can also find out public sentiment towards certain figures, data from Twitter, namely tweets of public opinion, there is a figure that can be used as data for sentiment analysis, now there is a lot of data on social media that can be used to find out public or customer sentiment towards certain products for example, and many more applications of data from social media. We have conducted a sentiment analysis of the 2019 Indonesian presidential election in previous research using machine learning algorithms. [1]. The results of our study can be used as an illustration of the sentiments of the Indonesian people towards the 2019 Indonesian presidential candidate, especially the Twitter social media user community.

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Another positive impact of the development of information technology is that we can feel more and more, processes that used to be mostly done offline or offline means to meet and meet face-to-face, with technological developments that are very rapid and fast, one by one the processes that used to be offline are now being carried out online, one of which is the teaching and learning process, which we have experienced together for the past two years, the whole world is at war with Covid-19, where one way to stop the spread of the virus is by not having direct contact with Covid-19 patients, meaning by not meeting each other and meeting face to face. It will reduce the risk of contracting Covid-19. Therefore, the teaching and learning process is one of the sectors affected by the call to reduce face-to-face contact. In the past two years, almost all learning and sharing of knowledge worldwide have been carried out online [2]–[6] with the development of information technology. These processes that used to be offline can now still be done online, although there are still many shortcomings and weaknesses. Information technology products in teaching and learning, for example, e-learning, learning media with animated images, audio and video, educational games, and video conferencing.

However, the development of information technology also has a negative impact on the community if they are less able to sort and select information. Because in cyberspace or the internet, people can be anyone, use a mask of goodness or a mask of evil, or even use both masks simultaneously. Therefore, various types of information can spread quickly through the internet from these irresponsible anonymous, false, or hoax information is widely spread on the internet, especially on social media such as Twitter, Facebook, and Instagram, because these social media do not go through review process by editors or experts. This is what causes fake information or hoaxes to be accepted by the public quickly without filters that can damage the unity and integrity of the nation [7]–[9]. Fake information packaged well and with convincing language becomes as if it is true is known as a hoax. During the COVID-19 pandemic, for almost two years, we have received information about the virus, especially COVID-19; the information circulating there is true and good, but not a few are also misleading and spread throughout the world [10]–[12], misleading information This causes anxiety and fear in the Indonesian people in particular and the world community in general.

Currently, the spread of false information or hoaxes in Indonesia is increasingly widespread, and many are being spread every minute. Hoaxes are usually widely spread in every significant event in Indonesia, from the campaign for the Indonesian presidential election to natural events being used as material for false information by those who are not responsible. Indonesia is a country with a diverse population and ethnicity with the large number of people and customs. The spread of hoax information can damage the unity and integrity of the nation [13]–[16]. Therefore, serious efforts are needed from all parties, especially the authorities, namely the government, to overcome the spread of hoaxes in the community. Prevention carried out by the Ministry of Communication and Information (KOMINFO) includes blocking sites that spread hoaxes and socializing about hoax news and its dangers in print media, television media, online media, and social media [16]. Researchers in the field of information technology, especially artificial intelligence, have tried to apply various methods to accurately detect hoax information that is massively spread on social media. Other researchers, such as Hasan, et al., developed an artificial neural network-based method for diagnosing potential centrifugal pump failures [17] and classifying the sleep state of a human being [18]. In addition, Hasan et al. also developed a new approach to the method of segmentation-based texture fractal analysis (SFTA), which is reported to have better accuracy than conventional SFTA [19]. Some of the methods that researchers widely use are unigram, bigram and include n-grams, for the most accurate method is the N-gram method; the way these method works is to tokenize sentences according to length N, so researchers determine how long N is in n-grams to get most accurate accuracy [20]–[22]. The weighting method most widely used by artificial intelligence researchers, especially natural language processing (NLP) in sentence extraction, is the term frequency-inverse document frequency (TF-IDF). The TF-IDF process calculates the frequency of occurrence of a word in a sentence and then compares it with the inverse of the data. The TF-IDF process also calculates how often a word is in a sentence; the more often the word appears, the smaller the weight value, meaning that the word is unimportant in a sentence, usually like conjunction (and, which, in, will, with, etc.) [22]–[25], and Passive aggressive algorithms are large-scale learning algorithms that are widely used in big data applications. They do not need the speed of learning like Perception. However, they have regularization parameters, unlike Perception. this algorithm is excellent for detecting fake information or on social media sites like Twitter and WhatsApp, wherein new social media data is added every second. [26]–[28]. Although there has been a lot of research in the field of artificial intelligence, especially regarding the detection of false information or hoaxes, there is still a need to research hoax detection to continue to improve the accuracy and effectiveness of hoax detection as an effort to reduce and prevent the spread of hoaxes in the community. In this study, we built a model to identify false information in Indonesian using an ensemble classifier which is a combination of the n-gram method, term frequency-inverse document frequency, and passive-aggressive classifier method. This is aimed to obtain the best accuracy and precision of the hoax detection among the proposed methods.

2- Methods

The first stage in this research is data collection. The data used in this study are tweets from both personal accounts and online news accounts with a total of 5000 tweet data taken using several keywords from several topics. Tweet data was collected from July to August 2021. The format for data collection uses labels as shown in Table 1.

Table 1: Label format used in data collection.

Feature	Description
Topic/theme	Topic or theme of tweet data
Keyword	Keyword used to search the data
Tweet text	Tweet text from search results
Image	URL of the image included in the tweet (if any)
URL	Tweet URL
Label	Labels on tweet data (valid or hoax)

The processes of identifying hoaxes are carried out using several trusted references. Figure 1 shows the procedures or steps taken in the identification of hoaxes used in this study.

Table 2: Data preprocessing.

Stage	Tweet data
Original tweet	Buat para ortu yg sdh mantu atau mau punya cucu atau ada ponakan2: "Vaksin Penyebab Autis" Buat para Pasangan... http://fb.me/6NaAYEKv4
After preprocessing	buat para ortu yg sdh mantu atau mau punya cucu atau ada ponakan2 vaksin penyebab autis buat para pasangan

2. The tokenization in this study uses n-gram, a model often applied in document processing. N-gram tokenizes sentences of length N [20]. The result of n-grams will be calculated using TF-IDF. In this study, sentence tokenization was applied using n-grams, and the number of features produced is shown in Table 3.

Table 3. The number of features resulting from n-gram tokenization.

N-gram type	Feature count
Unigram	4366
Bigram	11643
Trigram	12524
Unigram + bigram	16009
Bigram+ trigram	24167
Unigram + bigram + trigram	28533

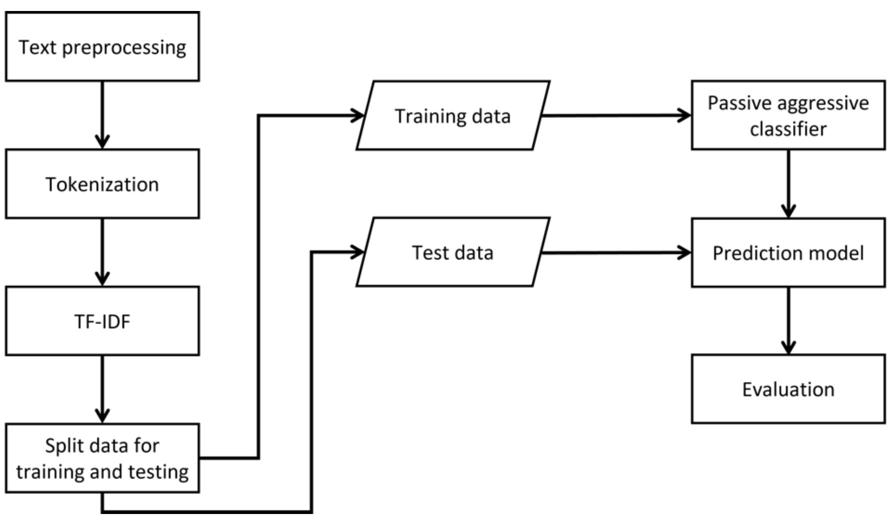

Fig. 1. Flowchart for hoax identification procedure using a combination of TF-IDF, n-gram, and passive aggressive classifier methods.

The stages in this research are as follows:

1. Several processes were carried out during the preprocessing stage to simplify and optimize the data processing. Some of the processes implemented include removing URLs, the # and @ symbols, punctuation marks, stop word lists, emojis, and numbers and changing the text into lowercase.
3. The next stage, TF-IDF, describes the importance of a word in a sentence or document. This process calculates the frequency of occurrence of a word and compares it with the inverse of the data [21]. This calculation allows an assessment of the role of a word in a sentence or document.
4. The stage before testing was splitting the data into training and testing. After the dataset was divided into training and testing data, the training data were trained

using a passive-aggressive classifier included in the category of online learning algorithms applied to machine learning. The passive-aggressive algorithms are a class of large-scale learning algorithms. They do not need a learning rate like Perception. They do, however, have a regularization parameter, unlike the Perception [28]. Furthermore, data testing was used for the prediction models. The testing process was conducted using four different schemes by dividing the dataset into training and testing data based on a ratio of 90:10, 80:20, 70:30, and 60:40, after referred to as splits 1, 2, 3, and 4, respectively.

5. The evaluation stage in this study uses the accuracy, precision, and recall from the experiments conducted.

Table 4. Confusion matrix.

Prediction	**Positive actual (1)**	**Negative actual (0)**
Positive prediction	True-positive (TF)	False-positive (FP)
Negative prediction	False-negative (FN)	True-negative (TN)

The process results were evaluated using the confusion matrix shown in Table 4. The test scenario is carried out using the n-gram feature (bigram, unigram, trigram, unigram + trigram, bigram + trigram, unigram + trigram) with various comparisons of the training and testing data.
The testing process was carried out using four different schemes by dividing the dataset into training and testing data based on a ratio of 90:10, 80:20, 70:30, and 60:40, referred to as split 1, 2, 3, and 4, respectively.

2-1- N-Gram

N-gram (adjacent n-gram) is a series of n characters or words extracted from a text. Usually, the n-grams that are often used are bigrams and trigrams, with the values of n being 2 and 3, respectively; N-grams are also called N-character chunks taken from a string [18].
Basically, the n-gram model is a probabilistic model designed by mathematicians from Russia in the early 20th century and later developed to predict the next item in a sequence of items. According to the application, items can be letters/characters, words, or others. One of them, the word-based n-gram model, is used to predict the next word in certain word order. In the sense that an n-gram is just a collection of words with each word having a length of n words. For example, an n-gram of size 1 is called a unigram; size 2 as “bigram”; size 3 as "trigram", and so on. In character generation, N-grams consist of n-character-long substrings of a string; in another definition, n-grams are n-character chunks of a string. This n-gram method takes n character pieces from a word that is continuously read from the source text to the end of the document.
For example the word "HOAX" can be broken down into the following n-grams:

unigram: H, O, A, X
bigram: HO, OA, AX
trigram: HOA, OAX and so on.

While in word generation, the n-gram method is used to take n-word pieces from a series of words (sentences, paragraphs, readings) which are read continuously from the source text to the end of the document.

2-2- TF-IDF (Term Frequency Inverse Document Frequency)

TF-IDF functions to convert text data into vectors by paying attention to whether a word is informative enough or not. TF-IDF makes words that appear frequently have a value that tends to be small, while words that occur rarely will have a value that tends to be large. Words that often appear are also called stopwords and are usually considered less important because they are only conjunction (at, will, with, etc.) [19].
TF-IDF stands for Term Frequency — Inverse Document Frequency. TF-IDF is a combination of 2 processes: Term Frequency (TF) and Inverse Document Frequency (IDF).

1. **Term Frequency (TF)**

Term Frequency (TF) counts the number of times a word appears in a document as shown in Eq. (1). Because the length of each document can be different [20], generally, the TF value is divided by the length of the document (the total number of words in the document).

$$tf_{t,d} = \frac{n_{t,d}}{Total\ number\ of\ terms\ in\ document} \quad (1)$$

Description
tf = frequency of occurrence of words in a document

2. **Inverse Document Frequency (IDF)**

After successfully calculating the Term Frequency value, we calculate using Eq. (2) the Inverse Document Frequency (IDF) value, which is a value to measure how important a word is [21]. The smaller the IDF value, the less important the word will be, and vice versa. IDF will assess words that often appear as less important words based on how they appear throughout the document.

$$idf_d = log(\frac{Number\ of\ document}{Number\ of\ document\ with\ term\ t'}) \quad (2)$$

After we have TF and IDF, next we can calculate the value of TF-IDF which is the product of TF and IDF using Eq. (3).

$$tfidf_{t,d} = tf_{t,d} \times idf_d \quad (3)$$

2-3- Passive Aggressive Classifier

Passive-aggressive algorithms include machine learning algorithms that are popularly used in big data applications [23].

The Passive-Aggressive Algorithm, which is usually used for large-scale learning, is also one of the online learning algorithms. In online machine learning algorithms, the input data come sequentially, and the machine learning model is updated sequentially, in contrast to conventional learning, where the entire training dataset is used at once.

This algorithm is advantageous in situations where there is a large amount of data, and it is computationally impossible to train the entire data set due to the sheer size of the data [22].

The Passive-Aggressive Algorithm is slightly like the Perceptron model because it does not require a learning speed. However, they do include a regularization parameter.

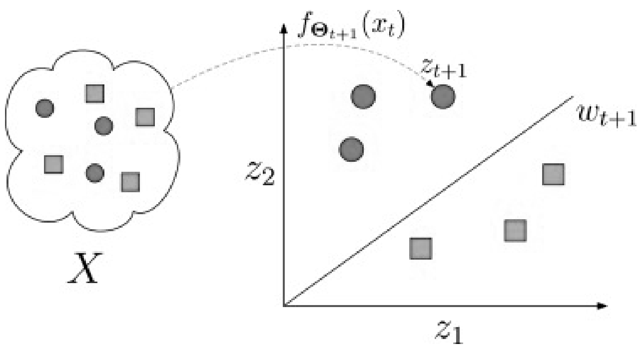

Fig. 2. Illustration Passive-Aggressive online learning

3- Results and Discussion

This research begins with the retrieval of data from Twitter. The data used in this study are tweets from personal accounts, group accounts, organizational accounts, and online news accounts, with a total of 5000 tweet data taken using several keywords from several topics. Tweet data were collected from July to August 2021. The following process is tokenization, which is the splitting of sentences into one token for each word. After being tokenized, each word is then given a weight using the TF-IDF word weighting method. Then enter the hoax news classification process or not with the Passive-Aggressive Classifier method; before entering the research dataset, testing is separated between hoax information and valid information, then the percentages obtained at the respective levels are 41% and 59%, for comparison. Next, the test data and training data are divided into 70% training data and 20% test data respectively from the dataset. The last stage of the research process is evaluating the prediction results, calculated using the accuracy model, namely the Confusion matrix.

In Table 5, the results of the hoax identification test are presented using several variations of the n-gram model for several combinations of the distribution of training data and test data, namely split 1, 2, 3, and 4 as previously defined split 1 = 90:10, split 2 = 80:20, split 3 = 70:30, and split 4 60:40. The trial application of the method used is to multiply the features using n-grams and divide the dataset by several division combinations. The comparison of the hoax information identification test results can be seen in Table 5.

Table 5: Comparison of the results of the hoax identification test.

N-gram model	**Accuracy (%)**			
	Split 1	**Split 2**	**Split 3**	**Split 4**
Unigram	90.98	91.39	90.41	87.68
Bigram	91.80	89.75	87.12	85.63
Trigram	81.97	79.51	80.55	80.49
Unigram + bigram	90.16	91.80	90.41	88.91
Bigram + trigram	89.34	89.75	87.12	84.80
Unigram + bigram + trigram	88.52	90.57	90.41	89.12

From Table 5, the highest accuracy value of all experiments is when the data split is split 1 with the bigram method. For the results of split 1, the bigram method is obtained with the highest accuracy value of 91.80%. The highest accuracy was obtained because in slip 1 the distribution of the training data was much larger than the test data, with a ratio of 90:10. The more training data, the easier the model is built to recognize the test data. As for split 2 data, the best accuracy is obtained by using a combination of unigram + bigram with an accuracy value of 91.8%. In testing the split 3 scheme, three models with n-gram tokenization received the same accuracy of 90.41%, namely unigram, unigram + bigram, and unigram + bigram + trigram. The maximum accuracy obtained in the split 4 data combination is lower than the maximum accuracy in the three previous data combinations. This is due to the lack of training data used in split 4, which is 60%.

Based on Table 5, we can see that the highest accuracy is obtained when using split 1 data division, which is 90:10 with the bigram model; the accuracy value reaches 91.80% for the test results on split 2 data with the unigram + bigram model the accuracy reaches 91.80%. After a series of trials, it was found that the words that had the most significant TF-IDF value of 10 from the bigram and unigram + bigram models, the results were dominated by words or sentences that asked readers to spread the news.

method combined with 90% training data distribution and 10% testing data from the dataset. This study's bigram tokenization method produces the highest accuracy because bigram tokenization splits sentences into two-word tokens. In this research data, most hoax information emerges from two-word pairs.

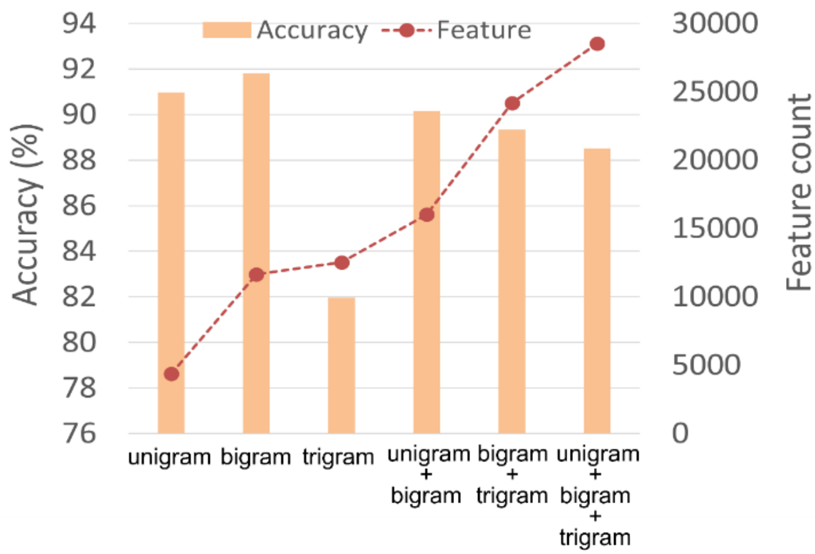

Fig. 2: Accuracy and feature count of hoax identification test results on several variations of n-gram on split 1 data combination.

From Figure 2, the more complex the n-gram used, the more features it has. However, from the several tests carried out, it can be seen that the results of the tests carried out on data split 1 show that the number of bigram features is still less than the number of features from unigram + bigram + trigram; it can be concluded that the number of features is not positively correlated with the accuracy obtained. It can also be seen in Figure 2 that trigrams which have more features than bigrams, get much lower accuracy.

Table 6. Words or word pairs that appear most often in hoaxes occurring in Bahasa Indonesia

Unigram	Bigram	Unigram + Bigram
'ortu' 'bocah' 'sungguh' 'miris' 'share' 'jiwa' 'kisah' 'ikut' 'mungkin' 'group'	'di share' 'share ke' 'ortu bocah' 'group ortu' 'ke group' 'hati miris' 'bisa di' 'bocah ini' 'akun facebook' 'dari sebuah'	['ke group' 'ortu bocah' 'di share' 'share ke' 'group ortu' 'bocah ini' 'ini datang' 'mungkin bisa' 'miris ini' 'sebuah akun']

Table 6 shows the words or word pairs that often appear in the Indonesian hoaxes used in this study. The highest accuracy in this study was when testing using the bigram

Table 7: Comparison between the performance of our method and those of other studies

Method	Accuracy	Precision	Recall	f-measure
This research	91.8	93.6	90.7	92.1
Zaman, et al. [29]	87.0	91.0	100.0	95.0
Pratiwi, et al. [30]	78.6	67.1	89.4	76.4

Zaman et al. [29] used the naive Bayes algorithm and user feedback to detect hoaxes, using the best ratio of training to test data, i.e., 70:30. Pratiwi et al. [30] used random repetition three times by applying the PHP-ml library and obtained the highest accuracy of 78.6%, with 70% training data and 30% testing data. A comparison of our classification performance with that of other studies is presented in Table 7. From the data shown in the table, it can be seen that there is an increase in the accuracy and precision of hoax detection testing with the proposed method in comparison to the two previous studies. This shows that our proposed method has the potential to be further developed and used in the detection of hoaxes in Bahasa Indonesia on various social media platforms.

4- Conclusions

Based on the results of this study, the model building can be used to identify hoaxes in Indonesia. The highest accuracy in this study was 91.8%, which was obtained when using a combination of tokenization bigrams with a split ratio of 1 and unigram + bigram with a split ratio of 2. The lowest accuracy of 79.51% was obtained when using a combination of trigram tokenization with a split ratio of 2. We also found that an increase in accuracy and precision of hoax detection testing can be achieved using the proposed method in comparison to other previous approaches.

Acknowledgments

This work was supported by a PTUPT 2021 research grant from the Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia [contract # 313/E4.1/AK.04.PT/2021].

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