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Hoax news identification using machine learning model from online media in Bahasa Indonesia

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Abstract: Information and communication technology that's developing is one of the main triggers of the information explosion today. Nowadays, various news content is not only easy to obtain but also easy to produce through various platforms on the internet, including popular online media, such as blogs and websites. So a lot of news content on blogs and websites that are currently being circulated leads to fake news content (hoaxes) that can mislead the perception and thoughts of the readers. Therefore, it is important to develop a system that can detect the presence of fake news content to minimize the losses caused by the presence of fake news content. In this study, the Naive Bayes algorithm is proposed as a machine learning model that will be used to detect fake news content in Indonesian language online media. As a result, the global accuracy value reached 71% with recall, precision, and F1-Score values as a whole above 70% which indicates that the proposed model can detect fake news content quite well.

Keywords: classification, fake news, hoax detection, online media, naïve bayes

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Introduction

The increasingly massive development of information and communication technology makes the world seems borderless [1]–[3]. As a result, information is now easier, faster, and more flexible to be accessed anywhere and anytime regardless of the location and place where the information is located. These developments certainly cannot be separated from the role of the internet which is currently evolving continuously and has even transformed into a major need for humans [4]–[6].

The internet, with its various advantages, is now able to become the main axis as well as an important factor in the development of modern and online-based information media such as social media and publication media such as websites and blogs. Websites and Blogs are currently growing and have become one of the effective information publication media, especially those related to news channels [7]–[9]. In fact, with the development of Websites and Blogs as media for publication at this time, the existence of traditional information media such as radio and television, as well as print media in the form of magazines, newspapers, and tabloids are now gradually being abandoned [10], [11].

Websites and blogs that make it easy for anyone not only to access information easily but also to be able to share information very quickly and freely have resulted in a massive information explosion [12]. The biggest impact caused is a change in mindset and the splitting of one's perception and belief in understanding the information received, this kind of thing, if left unchecked, can be the main trigger for a split between groups due to news and information whose validity is doubtful [8], [9].

It is important for someone to always increase awareness and vigilance when accessing news and information content through websites, blogs, and other online media to always ensure the truth and validity of the news displayed. Support for systems and applications that can assist someone in the early detection of fake news content is also very much needed to minimize the impact.

Until now, the researchers are still developing the systems and applications for the early detection of fake news content in online media. Various methods are proposed to find the maximum performance in detecting the presence of fake news content on a website page. One of the popular methods used in the research is the machine learning method [13]–[16]. Popular algorithms like Support Vector Machine (SVM) [13]–[15], Logistic Regression [14], [15], and Naive Bayes [5], [8], [13]–[16] are widely used and perform well when it comes to detecting fake news content in various datasets. As shown in research for detecting fake news from social media data like WhatsApp messaging and Facebook posts, the Application of SVM and the Naïve Bayes algorithm resulted in an accuracy of up to 93.5% [13]. Similar findings were discovered in a study conducted on Chile Earthquake 2010 datasets [14]. By using the Naive Bayes algorithm as a machine learning model, the resulting classification performance also shows a good value with an accuracy metric of 89.06% [14]. As a result of these many research, it is clear that the Naive Bayes algorithm has a high potential for detecting false news in a variety of datasets [13]–[16].

Unfortunately, based on the majority of studies, the detection of fake news using naive Bayes is widely applied to English datasets. Therefore, experiments on the usage of the Naïve Bayes classifier as a machine learning model for detecting fake news content in Indonesian language online media will be conducted in this study.

Methodology

The development of a machine learning-based fake news detection system for Indonesian language online media follows the development stages shown in Figure 1.

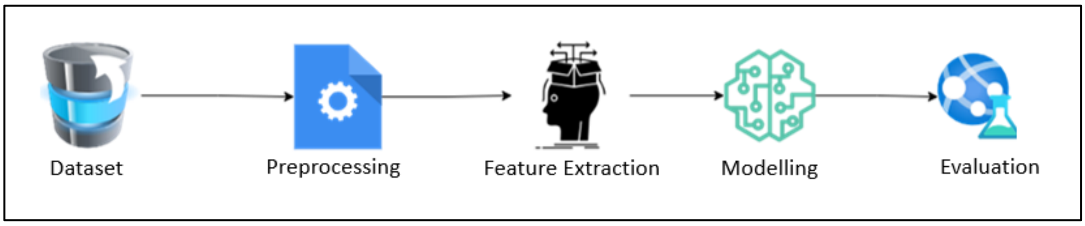

Figure 1. System development stages

In Figure 1, the stages of system development are carried out sequentially starting from the data acquisition process, then followed by the pre-processing stage (pre-process), followed by the feature extraction stage, the next is the modeling stage, and the last stage the performance evaluation. Each process carried out at each stage will be explained in detail and further through the respective sub-chapters.

A. Dataset

The dataset used in this study is the "Indonesian Hoax News Detection Dataset" which can be downloaded for free through the Mendeley Data Repository website page [8]. The dataset contains 600 Indonesian news articles consisting of 12 topics with 50 news articles for each topic. The dataset is also included in the binary classification where the first class is labeled as Valid News, and the second class is labeled as Fake News (hoax). The labeling process was carried out by 3 annotators manually with the final results taken using a vote tagging mechanism.

To label it as valid news, annotators use references sourced from Indonesian-language online media such as kompas.com, merdeka.com, tribunnews.com, and various other media that have credibility as media whose validity has been tested. While the label for fake news (hoax) will be given by the annotator when the news is obtained from media whose credibility is questionable [8]–[11].

B. Pre-processing

Pre-processing is the second stage that is carried out after the dataset is acquired. The purpose of doing this pre-processing stage is to understand the characteristics of the data, examine the data, and perform data cleaning so that the data will be ready to use at various stages of further processing. Some of the processes involved in the pre-processing stage are shown through the flow in Figure 2.

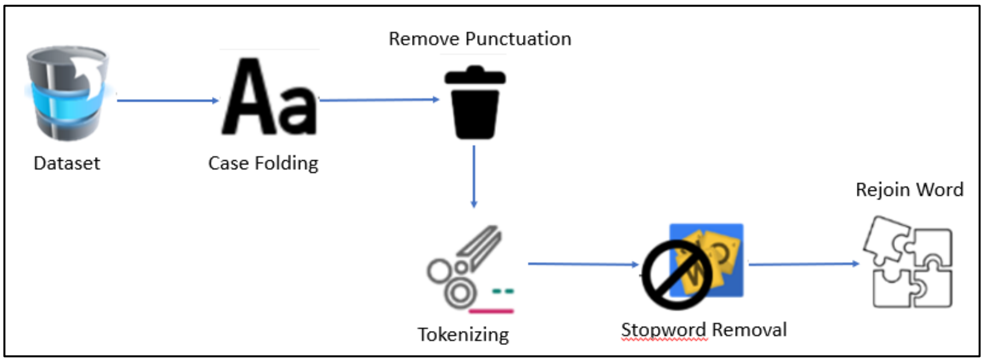

Figure 2. Pre-processing steps

The pre-processing stage in Figure 2 begins with the Case Folding process. This process is one of the common strategies and is widely used in data processing, especially for data in the form of text.

Case Folding is a process to change all the letters in the data, into lowercase, to maintain cosistency and generalize the structure of the text data used [9].

Data that has passed the Case Folding process then continue with the process of deleting punctuation marks. In addition to punctuation, various characters that have no meaning, and have no effect on processing text data will also be deleted and removed through the mechanism of the Remove Punctuation process.

Next is the tokenizing process, wherein in this process, the sentences in the data text will be cut into several words while removing certain characters that are not used in the study based on the presence of spaces in the data. The purpose of doing this tokenizing process is to find out what words are influential and tend to represent data from a certain class [3].

As a result of the tokenizing process, stop word removal will then be carried out to remove general words such as: "yang", "this", "is", "ke", and "di", where these words tend to have a high frequency of occurrence but do not have a specific meaning [8], [9].

The purpose of the stop word removal process is to speed up process performance because it reduces some common words, as well as to improve model performance because the data to be modeled is data that specifically contains important words that represent a certain class [4]–[6], [11]. For the stop word removal process carried out in this study, the researcher used the Indonesian language stop word list from Talla F.Z [17].

Finally, the process carried out from this pre-processing stage is the Rejoin Word process wherein this process has done to combines various words that have been processed through various previous stages so that they return to a unified whole sentence and become the main data that is ready to be processed using a machine model learning in the next processing stage [8], [9].

C. Feature Extraction

The Feature Extraction stage is the processing stage that is carried out after passing the pre-processing stage. In this study, the feature extraction process was carried out using the n-gram method and the Term Frequency - Inverse Document Frequency (TF-IDF) method. An n-gram is a form of feature extraction that works by breaking sentences into a set of n-word combinations [3], [7].

In this study, the use of the n-gram method is carried out in the form of trigrams (3-grams), where each sentence in the data will be cut by 3 words based on the proximity of the words, and each word resulting from the trigram process has then calculated the weight of each word using Term Frequency – Inverse Document Frequency (TF-IDF). The goal is to find out how big the relationship of a word is to the number of occurrences in a document.

Calculations performed using Term Frequency - Inverse Document Frequency are carried out by combining Term Frequency calculations to determine the frequency of occurrence of words in a document, as well as performing Inverse Document Frequency calculations to determine the frequency of occurrence of words in documents so that it can be seen how important the word is in a document [7]. The general equation for calculating TF-IDF is as equation:

$$Wdt = TFdt * IDFdt \tag{1}$$

The W symbol in equation (1) shows the amount of weight that the d-th document has, on the occurrence of the t-th word, in the entire data document. While TF shows the number of occurrences of words in a document, and IDF is Inverse Document Frequency which counts the occurrence of the t-th word in all documents.
To obtain the IDF value, the calculation process is carried out using the following equation:

$$IDF = log\ log\ \frac{N}{dft} \tag{2}$$

In quation (2), the symbol N indicates the number of data documents used, while dft indicates the number of documents containing the t-word.

D. Modeling

The steps for modeling the data are carried out after the feature extraction stage is carried out. At this stage, machine learning algorithms are used to model the data, which makes the system seems to be able to predict whether a news item is included in the category of valid news, or fake news (hoax).

In this study, the machine learning model used is Naïve Bayes. Naïve Bayes is included in one of the popular algorithms used to overcome various problems related to text classification [2], [9], [13], [16]. This is of course inseparable from the workings of the Naïve Bayes Algorithm which uses Probability and Statistics to model and predict the occurrence of a word in certain data class categories [2], [9]. Equation (3) shows the general equation of the Naïve Bayes Algorithm:

$$\mathrm{P(A|B)} = \frac{\mathrm{P(B|A)\ P(A)}}{P(B)} \tag{3}$$

Where:
$\mathrm{P(A|B)}$: Posterior Probability
$\mathrm{P(B|A)}$: Likelihood Probability
$\mathrm{P(A)}$: Prior Probability
$\mathrm{P(B)}$: Evidence Probability

In equation (3), Posterior probability shows the prediction of the probability value based on the occurrence of one event based on information from other events. Likelihood probability describes an opportunity that states the degree of the possible influence of information on the occurrence of another event. The opportunity contains the probability value of the occurrence of an event that has been previously believed and it could be that the event is influenced by other events, lastly, Probability Evidence shows a constant comparison measure based on the probability of event information [16].

E. Evaluation

The final step is evaluation, which is used to determine the performance of the model proposed in the research. The Confusion Matrix is one of the most commonly used assessment measures for evaluating classification performance [18].

Table 1. Binary classification confusion matrix

Predicted Class	Actual Class	
	Positive	**Negative**
Positive	True Positive [TP]	False Positive [FP]
Negative	False Negative [FN]	True Negative [TN]

As shown in Table 1, the confusion matrix has a square shape that maps each class with other classes on both the actual and the predicted side of the system [19]. In general, there are four (4) parts to the process of mapping data classes in binary classification, namely:

- True Positive
  True Positive (TP) indicates how much of the data predicted by the system is positive, with the actual value also being positive.
- True Negative
  True Negative (TN) shows how much data the system predicts as negative values, and the actual values are also negative.
- False Positive
  False Positive (FP) indicates how much of the data is predicted by the system as positive values, while the actual values are negative.
- False Negative
  False Negative (FN) shows how much of the data is predicted by the system as a negative value, while the actual value is positive.

The confusion matrix will be used to determine the performance indicators of the classification model, such as accuracy, precision, sensitivity, and F1-Score (Harmonic Mean) to determine a machine learning model's success and classification performance [18], [19].
through equation (4), the performance of the classification model based on the accuracy metric

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

The accuracy measure shows how effectively the classification performance, as measured by the percentage value provided by the algorithm, predicts properly based on all prediction findings [19].

In addition, the accuracy metric will be used to evaluate the classification model's performance, as can a precision value calculated using the equation (5).

$$precision = \frac{TP}{TP + FP} \tag{5}$$

The precision value is a measure for evaluating the classification performance in terms of the model's dependability in making positive predictions. In other words, by computing the accuracy number, one may determine how effectively the model identifies fake news from the total results projected to be false.

The next metric that can provide information about the classification model's success rate is the sensitivity matrix, which is used to calculate the proportion of data predicted to be positive by the system out of all data with a positive label with the equation (6).

$$sensitivity\ (recall) = \frac{TP}{TP + FN} \tag{6}$$

the F1-Score was used in this study using equation (7) to assess the proportion of the calculated precision and sensitivity values [19].

$$F1\,Score = \frac{2 * Precision * recall}{precision + recall} \tag{7}$$

Results and Discussions

Research related to the analysis and detection of fake news content in Indonesian language online media has been carried out according to the methodology described in the previous section. This research was conducted with an analytical approach using a classification technique to determine a news story in the Indonesian language or online media is included in the category of valid news or fake news (hoax). The dataset used in this study was carried out using the "Indonesian Hoax News Detection Dataset" [8], with the data form as shown using the Table. 2. Some examples of the Indonesian Hoax News Detection Dataset.

Table 2. Examples of the Indonesian hoax news detection dataset

No.	News	Tagging
1	Jakarta, Di jejaring sosial, banyak beredar informasi yang menyebut lele sebagai ikan paling jorok. Dalam sesuap daging ikan lele, terkandung 3000 sel kanker.	Valid
2	Bahaya Mengkonsumsi Ikan Lele Yang Mengandung Sel Kanker - Lele adalah sejenis ikan yang hidup di air tawar. Ikan lele mudah dikenali karena tubuhnya yang licin, agak pipih memanjang, ...	Hoax
3	Akhir-akhir ini kita sering mendapat broadcast informasi via BBM tentang Cara pertolongan pertama pada penderita Stroke, bunyi pesan broadcast tersebut kira-kira sebagai berikut: orang yang kena STROKE mendadak ...	Hoax
4	Mudah melengkungnya casing iPhone 6 Plus menjadi perbincangan hangat belakangan ini. Dan itu bukan hisapan jempol semata. Sudah ada pengguna iPhone 6 Plus yang mengalami kejadian tersebut. ...	Valid
5	Sungguh para oknum Konsultan Jenderal Republik Indonesia (KJRI) di Davao, Filipina ini keblinger. Mereka tega membakar dadak merak Reog Ponorogo beserta gamelan pengiringnya karena dianggap barang mengandung berhala. Tindakan KJRI itu jelas-jelas telah menghancurkan warisan budaya luhur nenek moyang kita dan tidak tahu tentang sejarah Reog Ponorogo yang sudah mendunia dan menjadi aset budaya Bangsa Indonesia di UNESCO. ...	Hoax

Table 2 shows some examples of datasets in the Indonesian Hoax News Detection Dataset. In the dataset, there are 2 main columns, namely news, and tagging.

The news column contains various articles that have been taken from various online news sources in Indonesian according to the topic that is the focus of the preparation of the dataset, while the tagging column is a label given to news articles by the vote tagging process carried out by the annotator during the data labeling process.

From the dataset that has been acquired, the next step that needs to be done is to examine the dataset to find out important information that can support the analysis process before entering the next processing stage.

Some important things such as information from the distribution of data classes are mandatory things that need to be known so that the analysis process runs more optimally.

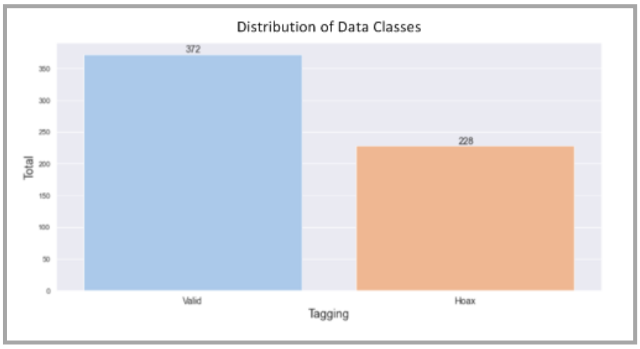

Figure 3. Distribution of data classes

Figure 3 shows that the distribution of data classes between fake news (hoax) and valid news has unbalanced characteristics. For news with valid data class, it has a larger amount of 372 data, while data with a label as fake news (hoax) is 228 data.

Next, the process will be carried out at the pre-processing stage, where the dataset will be processed using a case-folding mechanism to generalize the structure and maintain data consistency. The following is an example of news data that has gone through the case folding process.

```
Before case folding :
Dalam sesuap daging ikan lele, terkandung 3000 sel kanker. Itulah kabar bera
ntai yang beredar di jejaring sosial yang menyebut ikan lele adalah ikan pal
ing kotor. Berita ini bohong 100 persen. Fakta menyebutkan ikan lele rendah
kolesterol. Ikan lele yang beredar di pasaran umumnya dibudidayakan di kolam
-kolam, yang mestinya bisa dikendalikan agar bebas dari pencemaran. Saat ini
belum ada penelitian yang menyatakan jika memakan lele dapat memicu kanker,
tegas dr Dradjat R Suardi, SpB(K)Onk, ahli kanker dari Perhimpunan Onkologi
Indonesia.

After case folding :
dalam sesuap daging ikan lele, terkandung 3000 sel kanker. itulah kabar bera
ntai yang beredar di jejaring sosial yang menyebut ikan lele adalah ikan pal
ing kotor. berita ini bohong 100 persen. fakta menyebutkan ikan lele rendah
kolesterol. ikan lele yang beredar di pasaran umumnya dibudidayakan di kolam
-kolam, yang mestinya bisa dikendalikan agar bebas dari pencemaran. saat ini
belum ada penelitian yang menyatakan jika memakan lele dapat memicu kanker,
tegas dr dradjat r suardi, spb(k)onk, ahli kanker dari perhimpunan onkologi
indonesia.
```

Figure 4. Case folding process

Figure 4 shows the news data before and after the case folding process is carried out. For news data that have not gone through the case folding process, it can be seen that the arrangement of letters in news sentences still uses a combination of uppercase and lowercase letters, while for news data that has gone through the case folding process, it can be seen that there are similarities in the structure of letters for each sentence using lowercase letters.

After going through the case folding process to make the structure of the letters the same, the next step is to carry out the remove punctuation process to remove all punctuation marks contained in news sentences. The results of the removal punctuation process are shown in Figure 5.

```
case folding:
dalam sesuap daging ikan lele, terkandung 3000 sel kanker. itulah kaba
r berantai yang beredar di jejaring sosial yang menyebut ikan lele ada
lah ikan paling kotor. berita ini bohong 100 persen. fakta menyebutkan
ikan lele rendah kolesterol. ikan lele yang beredar di pasaran umumnya
dibudidayakan di kolam-kolam, yang mestinya bisa dikendalikan agar beb
as dari pencemaran. saat ini belum ada penelitian yang menyatakan jika
memakan lele dapat memicu kanker, tegas dr dradjat r suardi, spb(k)on
k, ahli kanker dari perhimpunan onkologi indonesia.

No-punctuation:
dalam sesuap daging ikan lele terkandung 3000 sel kanker itulah kabar
berantai yang beredar di jejaring sosial yang menyebut ikan lele adala
h ikan paling kotor berita ini bohong 100 persen fakta menyebutkan ika
n lele rendah kolesterol ikan lele yang beredar di pasaran umumnya dib
udidayakan di kolamkolam yang mestinya bisa dikendalikan agar bebas da
ri pencemaran saat ini belum ada penelitian yang menyatakan jika memak
an lele dapat memicu kanker tegas dr dradjat r suardi spbkonk ahli kan
ker dari perhimpunan onkologi indonesia
```

Figure 5. Remove punctuation process

Figure 5 shows the results of the remove punctuation process which was carried out at the pre-processing stage after the case folding process was carried out. The remove punctuation process is done by using a regular expression to replace all data other than characters and numbers with spaces. The results of the removal of punctuation will be followed by a tokenizing process or a process that will break the sentence into word order. By doing the tokenizing process, we can find out which words are dominant and have the highest frequency of occurrence in the document, as shown in Figure 6.

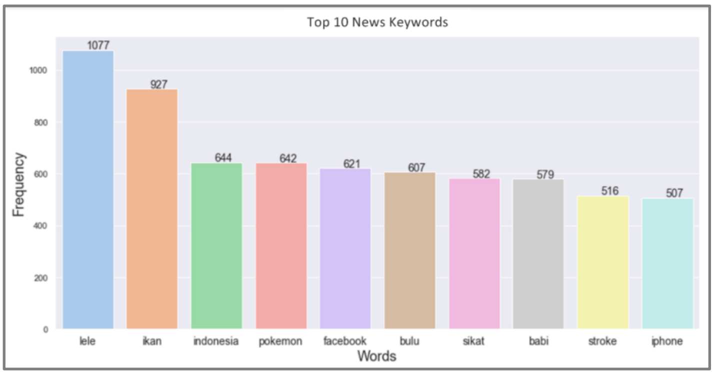

Figure 6. Top ten (10) news keywords

Figure 6, shows the result of the top ten (10) keywords that are dominant and have the highest frequency of occurrence in the document. It is what we have from doing the tokenizing process. The word "lele" have 1077 frequency in all documents, the word "ikan" have 927 frequency in all documents, the word "Indonesia" have 644 frequency in all documents, and the word "pokemon" have 642 frequency in all documents, and so on. Those keywords help recognize the main topics discussed.

After going through the tokenizing process, the next step is a stop word removal process which aims to eliminate words with a high frequency of occurrence but do not have a specific meaning that represents a class of news data. In this case, the stop word removal process is carried out using an Indonesian stop word list from Talla F.Z [12].

The last stage, after the stop word removal process, is to recombine various words that have been processed in the previous stage, so that they return to a unified whole sentence and become data that will be processed for the next processing stage.

The data that has gone through the pre-processing stage will then be extracted using the trigram method with naïve Bayes as the algorithm for the modeling process. In these steps, the author uses multinomial naïve Bayes because its model has been designed to determine term frequency i.e. the number of times a term occurs in a document. Considering the fact that a term may be pivotal in deciding the sentiment of the document, this property of this model makes it a decent choice for document classification. Also, term frequency helps decide whether the term is useful in our analysis or not. Sometimes, a term may be present in a document many times which increases its term frequency in this model but at the same time, it may also be a stopword that potentially adds no meaning to the document but possesses a high term frequency so, such words must be removed first to gain better accuracy from this algorithm [15]. Based on the results of multinomial calculations, naive Bayes and the results are known to have performance values as shown in the Figures 7.

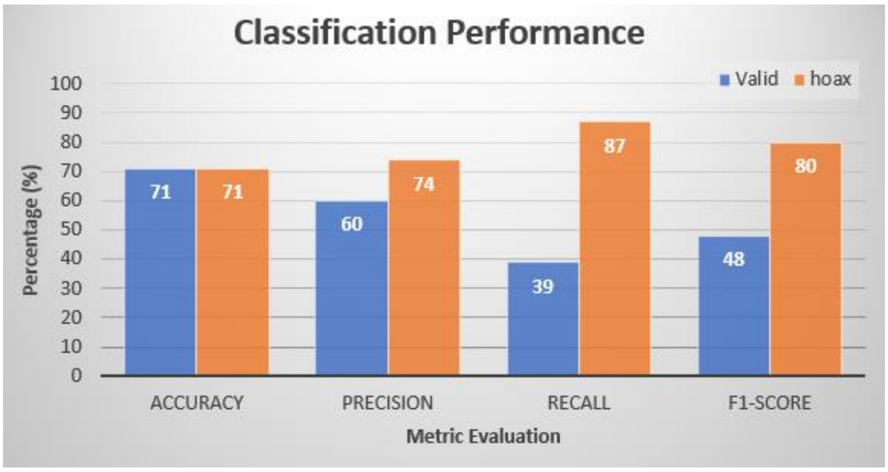

Figure 7. Metric evaluation

Figure 7 shows the performance of a machine learning model based on four (4) forms of measurement metrics, namely accuracy, precision, sensitivity, and F1-score. The performance value is obtained based on the distribution of training data and testing data with a proportion of 70:30, where 70% of the data will be used as training data used to build the model, while 30% of the other data will be used as testing data used to test the performance of the model.

Based on the results of the experiments carried out, as shown in Figure 7. the global accuracy value obtained is 71.00%. However, when viewed based on the value for each class of data, the value of precision, sensitivity (recall), and F1-Score produced shows a fairly good performance in detecting fake news (hoax) in experimental data.

The precision, sensitivity, and F1-score values obtained to determine the performance of the proposed machine learning model are calculated using the equation as described in the previous chapter. The precision value for valid news is 60%, while for hoax news it is 74%. This shows that there is a link between global accuracy results and the system in detecting fake news content (hoax) better when compared to valid news content. Likewise, the value generated on the sensitivity and F1-Score shows that the highest value is obtained in detecting the presence of fake news content (hoax) in the data. Therefore, when viewed from the value of precision, sensitivity (recall), and the resulting F1-Score, the system's prediction of fake news shows a better performance than the system's prediction of valid news.

Conclusion

Experiments related to the detection system of fake news content on Indonesian-language online media using machine learning models have been completed in this study. Naïve Bayes as the algorithm proposed as a model to predict a new invalid news content included, or fake news (hoax) produces a global accuracy value of 71%.

In addition, an experiment conducted on 600 news data using the Indonesian Hoax News Detection Dataset, obtained the respective performance values, namely a precision value of 74% for fake news detection, and 60% for valid news. A sensitivity value of 87% for hoax news is higher compared to the detection of valid news which produces a sensitivity value of 39%. For the F1-Score value, the detection of fake news (hoax) is 80%, while the detection of valid news is 48%.

Based on these results, it is known that the proposed model can be used to detect fake news content in Indonesian language online media quite well.

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