

# Indonesia's Fake News Detection using Transformer Network

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## ABSTRACT

Fake news is a problem faced by society in this era. It is not rare for fake news to cause provocation and problems for the people. Indonesia, as a country with the 4<sup>th</sup> largest population, has a problem in dealing with fake news. More than 30% of the rural and urban population are deceived by this fake news problem. As we have been studying, there is only a little literature on preventing the spread of fake news in Bahasa Indonesia. So, this research is conducted to prevent these problems. The dataset used in this research was obtained from a news portal that identifies fake news, turnbackhoax.id. Using Web Scrapping on this page, we got 1116 data consisting of valid news and fake news. This dataset will be combined with other available datasets. The dataset is then processed by eliminating irrelevant words and dividing the data into training and testing data with a ratio of 80:20. All neural network methods use word embedding with Word2Vec with 50 dimensions. The methods used are CNN, BiLSTM, Hybrid CNN-BiLSTM, and BERT with Transformer Network. This research shows that the BERT method with Transformer Network has the best results with an accuracy of up to 90%.

## CCS CONCEPTS

• Computing methodologies → Natural language processing.

## KEYWORDS

fake news, BERT, Transformer Network

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## 1 INTRODUCTION

In the era of globalization, the internet has been used in the world widely. People can get many information through various sites. This information can be obtained through news portals, articles on the internet, and social media. Unfortunately, not all of this news and articles contain correct and valid information. This invalid information is called "fake news". Fake news is false information that is formed like a format of news media content without proper processing by the news agency [14]. The spread of fake news is an important concern. Fake news could be a threat to journalism and freedom of expression. Fake news can be a provocation or slander against an important organization or person. A study from Stanford University discussed social media and fake news during the US presidency in 2016. This study revealed that fake news sites had been visited up to 159 million times during that time [3]. To prevent public misunderstanding about news, this research is attempting to provide the best accuracy in detecting fake news through deep learning.

There is a wide variety of literature that develops ways of preventing the spread of fake news. These methods are text classification, network analysis, and Human-Machine Hybrid integration. As the implementation had been through, these methods have their own advantages and disadvantages in their implementation [16]. Indonesia is one of the countries that facing widespread fake news. A survey showed that 46% to 61% of rural knew provided fake news. Uniquely, the urban has a higher proportion than the rural. And there are 38% to 61.1% of rural believe the fake news and 45.3% to 79.6% of urban believe the fake news [15]. This sufficiently proves that the spread of fake news in Indonesia is quite concerning. This study will discuss one of the ways that can be used to indicate fake news. Using Bahasa Indonesia as an instrument, we use several methods to detect fake news.

With such a large spread, a system that can detect thousands or perhaps millions of data at a time is needed. The amount of data scale, distribution, diversity, and/or timeliness requires, shows that this is a field of Big Data Analytics [9]. Any technology that can be applied properly can have an advantage. Unfortunately, big data is very difficult to deal with [6]. So that in applying it, we need the right method in analyzing it. We compiled various methods that can be used in deep learning to indicate fake news. Study A. Wani, et al. [21] discusses the detection of covid-19 fake news. Using the dataset Constraint @ AAAI2021 - COVID19 Fake News, the dataset contains news in English. The method used is two approaches,

namely the simple model approach of deep learning (CNN, LSTM, BiLSTM + Attention, HAN) and the Transformer based model (BERT and DistilBERT). This study results in the Transformer based having a better level of accuracy. Despite the results of other methods, CNN does not have poor accuracy either, it was 93.5%.

There are only a few systems for detecting fake news in other languages than English. A study by Hoossain, et al., using a Bangladesh language dataset with 3 approaches, namely baseline, traditional linguistic features with SVM, and neural network models (CNN, LSTM, and BERT) [12]. This study produces a neural network model with CNN that has good accuracy with a total news class with a precision of 98%, recall of 10%, and an F1-Score of 99%. Another study that discusses the detection of fake news is a study provided by Jiang, T., et al. [13]. This study uses a dataset consisting of 44898 articles with 21417 original news and 23481 fake news with two classes in them. Using the BiLSTM method and text embedding GloVe, the accuracy obtained is 99.82%. Based on these studies, we used transformer model in the hope of having better accuracy. This study also focused on detecting fake news in Bahasa. In addition, we use datasets available on the internet and scrapping on the turnbackhoax.id website.

## 2 RELATED WORK

The first research was conducted by Kaliyar in 2018 [19] focused on fake news on social media. The dataset used in research such as from Kaggle. In this study, machine learning algorithms such as Naïve Bayes, decision trees, and deep learning are used, such as shallow convolutional neural networks (CNN). This study also used feature extraction such as TF-IDF and then also used word embedding. The results obtained using CNN yielded an accuracy of up to 98.3%.

The next research on fake news was conducted by Ahn [1]. The dataset was collected via the internet with a 50000 million data with a 50:50 division between classes. In the signing process, the word piece model (WPM) method is used. The model used in this study is BERT as one of the state-of-the-art models. The results obtained in this study resulted in a ROC curve value of 0.838. So that the model built was good at detecting fake news. Other research that we have been read is the detection of fake news using a semi-supervised learning approach [5]. This study, using a dataset with 50 rows of data with 75 data with fake labels, and 75 with real labels. Then for embedding in the research using GloVe pre-trained. Then the algorithm model used is Graph Convolutional Networks and Attention Graph Neural Network. The results show that many of these algorithms have better results when compared to machine learning algorithms such as SVM and Random Forest. The highest accuracy is obtained with the number 84.94%.

Research related to fake news was conducted by Ahuja [2]. In this study, using the dataset available in Kaggle. The total dataset is 12953 for fake news and 15712 for news labeled true/real. This study using the GloVe embedding. Then the proposed algorithm uses a Hierarchical Attention Network added with stacked bidirectional Gated Recurrent Units (GRU). The results show that the proposed model produces a better model than other deep learning models. The proposed model succeeded in obtaining an accuracy of 93.83%

while the comparison algorithm, for example, LSTM, only obtained 90.31%.

The next research was conducted by Aslam [4]. In this research, using the "LIAR" dataset in which there are 12.8K, around 2053 for data labeled true and 2504 for fake labels were selected so that the total dataset reached 4557. In the preprocessing stage using wordnet as tokenizer and WordNetLemmatizer as lemmatization. The algorithm used is a deep learning ensemble model, namely, BiLSTM-GRU and dense deep learning. The result is an accuracy of 89.8%. Which shows better results than other algorithms such as LSTM and CNN.

The next research related to fake news was conducted by Girgis [11]. In this study, the WILD dataset contains 12,836 statements. The models used to detect fake news are recurrent neural networks (vanilla, GRU) and long-short-term memories (LSTM). The model built produces an accuracy that is around 21.7%. The next research was conducted by Fang in 2019 [10]. The dataset used in this study comes from fakenews.mit.edu where there are 12,228 fake news and 9,762 non-fake news. In this study, using word embedding, GloVe, and Word2vec. Then this study uses a model of self-multi-head attention and convolutional neural network (SMHA-CNN). The model was evaluated using a 5-fold CV with an accuracy of being able to reach 95.9%.

The research we conducted is using Bahasa Indonesia as the instrument. Research that related to a similar case is the research from [18]. The research is case folding, tokenizing, stopwords removal, and term frequency at the preprocessing stage. After that, this research uses Naïve Bayes in its main process. Using 600 news items, the average accuracy obtained is 82.6%. Dynamic testing was performed with 60 news and resulted in conformity of 68.3%.

Another research that uses Bahasa Indonesia as a dataset is research from [22]. This research uses a method that is similar to the previously described research, they are Reader feedback and Naïve Bayes method. The author of this study considers Naïve Bayes with 10-fold cross-validation to be the method that has the best accuracy based on the literature collected. Thus, by using these two methods and the dataset obtained through <https://turnbackhoax.id> with 250 news, this research produces an accuracy of 87%, 91% of precision, and 95% of f-measure. According to the lack of research on fake news detection in Bahasa Indonesia and the lack of methods used. This study offers a different method from other fake news detection research in Bahasa Indonesia. We also use a transformer for this research. We use it because based on literature, it affects increasing the accuracy. Additionally, this research conducted scrapping on the <https://turnbackhoax.id> website with more news than other research to get a better tough result.

## 3 METHODOLOGY

### 3.1 BERT

BERT or Bidirectional Encoder Representations from Transformers is a form of the model in transformers that applies bidirectional training then combines the context from the left and right layers [8]. RNN and Transformer have a similar architecture in that there are encoders and decoders. BERT applies a transformer architecture, where the focus is Attention. Attention is a focus where we determine the main focus or context of a sequence. For example, instead

of translating between languages, the encoder will also write down important keywords/words. Attention is also a function used to map queries and follow key-value and output pairs, all of which are in vector form [20]. The equation of Attention can be seen in Eq (1).

$$\text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right) V \quad (1)$$

Where Q is the matrix that builds the query (contains a vector of each word), K is the key, V is the value itself. Softmax is a activations in deep learning which is useful for the weight of attention leading to between 0 and 1 (the probability).

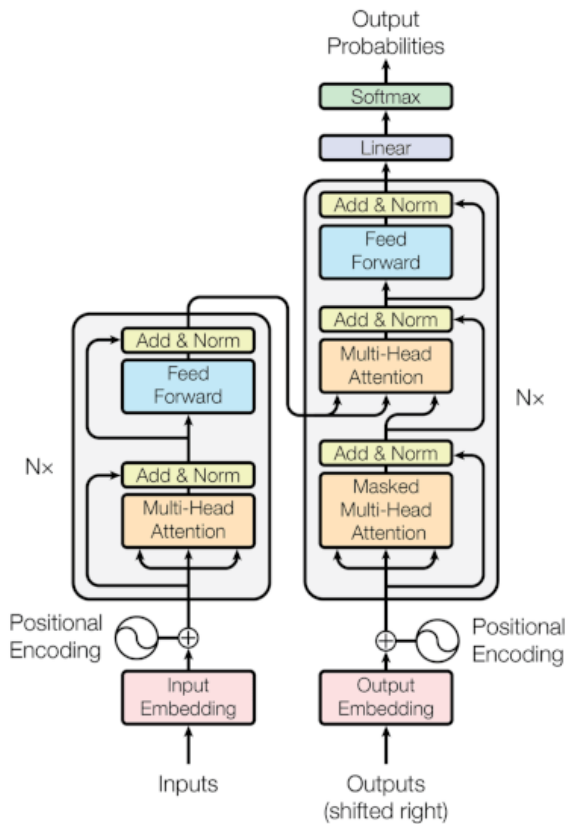


Figure 1: Transformer Network. Photograph by [20]

BERT can also be understood as a stack of transformer architecture. BERT has two models, BERT Base, which has 12 layers of encoder layer stacks, and BERT Large which has 24 stacks of encoder layers. BERT Base has about 110M parameters while BERT Large has 340M parameters [7]. In BERT, two steps are followed, called pre-training and fine-tuning. Pre-training is the stage where the model is trained using unlabeled data (unsupervised task) through pre-training tasks, while fine-tuning is a model initialized with the parameters of previous training results, and fine-tuning using data that are already labeled. In the pre-training, there is one task, namely, the LM Mask where 15% of the words will be changed by a [MASK], then the model will make predictions in the form of a probability value for the possible words that can be filled. The

Table 1: Default Hyperparameter for BERT

Hyperparameter	Value
Loss function	Categorical-cross entropy
Learning rate	2e-05
Optimizer	Adam
Number of epochs	50
Batch size	16

Table 2: CNN Layered Architecture

Layer	Output Size	Param Number
Embedding	1000 x 50	2157800
Conv1D	999 x 32	3232
Dropout	999 x 32	0
Global Maxpool 1D	32	0
Dense	2	66

second task, namely, Next Sentence Prediction (NSP), is a mechanism for predicting the next sentence from a previous sentence. Where during the training process 50% of the input came from the original document, while 50% was chosen randomly. The purpose of training using these two tasks is to produce the smallest loss function value.

### 3.2 CNN

A convolutional neural network (CNN) is a deep learning method that can be applied to classify text documents. The first layer is the embedding layer where the input results come from the Word2Vec process. We use 1 layer of Conv1D layer with kernel size 2. Conv1D is used because it can be used to process natural language. The Detail of CNN architecture that we use in this study can be seen in Table 2.

### 3.3 BiLSTM

BiLSTM is a development of the LSTM model where two layer processes each other in a reverse direction, this model is excellent at recognizing patterns in sentences as each word in the document is processed sequentially. The layer underneath moves forward (forward), namely understanding and processing from the first word to the last word while the layer above it moves backward (backward), namely understanding and processing from the last word to the first word. With there is a layer of two opposing directions then the model can understand and take the perspective of the word preceding and forefront, so the learning process will be deeper which impact on the model will be more understand the context in the document. Detail of The BiLSTM architecture that we use in this study can be seen in Table 3.

### 3.4 Hybrid CNN-BiLSTM

Another approach to deep learning is to combine models. In this study, we tried combining the CNN and BiLSTM models. The details of the Hybrid CNN-BiLSTM architecture can be seen in Table 4.

**Table 3: BiLSTM Layered Architecture**

Layer	Output Size	Param Number
Bidirectional	1000 x 256	184320
Global Maxpool 1D	256	0
Dropout	256	0
Dense	2	514

**Table 4: Hybrid CNN-BiLSTM Layered Architecture**

Layer	Output Size	Param Number
Embedding	1000 x 50	2157800
Conv1D	999 x 32	3232
Dropout	999 x 32	0
Maxpool1D	499 x 32	0
Bidirectional	499 x 256	165888
Global Maxpool 1D	256	0
Dropout	256	0
Dense	2	514

**Table 5: Default Hyperparameter for BERT**

Hyperparameter	Value
Loss function	Categorical-cross entropy
Learning rate	2e-05
Optimizer	Adam
Number of epochs	50
Batch size	16
Dropout	0.5

After discussing the entire deep learning architecture that will be used, we will then show the hyperparameters to be used for deep learning models which can be seen in Table 5.

## 4 EXPERIMENTAL SETUP

### 4.1 Dataset details

This research uses 3 datasets that are combined into one. The first dataset is a dataset obtained from Mendeley with 600 data, containing 372 valid news stories and 228 fake news. The dataset can be accessed on the <https://data.mendeley.com/datasets/p3hfgr5j3m/1>. The next dataset is a dataset derived from GitHub, Hoax News Classification. The dataset that can be accessed at <https://github.com/pierobeat/Hoax-News-Classification> has 500 data with 250 valid news and 250 fake news. While the last dataset is a dataset obtained through scrapping on <https://turnbackhoax.id> page. Starting from the 25th of April 2021, this page has 35 categories with 6973 data. By considering the content of each category, we use the "Benar" category as valid news with 433 data and the "Hoax" category with 683 data as fake news. The scrapping results can be accessed at <https://github.com/JibranFawaid/turnbackhoax-dataset>. The features that we use from the three datasets are the Label, Headline,

and Body of each news. There are examples of fake news and valid news that we have studied. An example of fake news:

*"Siapa yang tidak tahu dengan lele, ikan yang satu ini merupakan favorit bagi banyak orang karena memiliki rasa yang enak dan memiliki tekstur daging yang lembut namun ternyata lele ikan paling kotor..."*

*("Who does not know catfish, this one fish is a favorite for many people because it has a good taste and has a soft meat texture, but it turns out that catfish is the dirtiest fish...")*

Besides invalid news, valid news has its own pattern. Example of valid news:

*"Mungkin Anda pernah membaca artikel atau sekadar pesan berantai soal pertolongan pertama penderita stroke dengan menusukkan jarum ke ujung jari hingga berdarah. Jangan menelan mentah informasi ini dan melakukannya. Diterangkan dr Astried Indrasari SpPD..."*

*("Maybe you have read an article or just a chain message about first aid for stroke patients by sticking a needle into the tip of a finger until it bleeds. Do not swallow this information raw and do it. Explained by Dr. Astried Indrasari SpPD...")*

### 4.2 Preprocessing of Dataset

Using 3 datasets combined previously, we divide the training and testing data with a ratio of 80:20. As the result, the data are divided into 1772 training data and 444 testing data. In the next stage, we perform a cleaning process on the dataset using the regex library. This method is functionally for correcting the data through an algorithm. So that it can save costs and time to be used next. As we know, that in the dataset, words need to be ignored in processing, such as the words "dan" (and), "atau" (or), "tapi" (but), etc. So, we do a Stopword removal to delete these words to increase the processing speed and performance that will be performed using the Sastrawi library.

### 4.3 Word Embedding

All neural network methods use word embedding with Word2Vec with 50 dimensions. Word embedding is used as a technique to convert a word into a vector or array consisting of a collection of numbers. The Gensim library [23] was chosen as the word embedding process. Gensim is a library that can be used for processing natural language and unsupervised topic modeling.

### 4.4 Transformers

The fine-tuning strategy in BERT uses an existing pre-trained model. Pre-trained BERT-Multilingual-Cased from Hugging Face [8] was chosen in this study because it provides various languages including Bahasa. The details of the BERT-Multilingual-Cased layer can be seen in Table 6.

### 4.5 Results and discussion

In this study, we use three data sources with a total data reaching 2,216 with a distribution of 1,055 as valid data and 1,161 as false data. The dataset is then divided into data with a ratio of 80%: 20% for training and testing data sequentially. So that the total training data used is 1772 and 444 test data. The implementation uses Google

**Table 6: BERT-Multilingual-Cased**

Details	Value
Language	104
Layer	12
Hidden Layer	768
Head	12
Parameter	110

**Table 7: Comparison of Neural Network and Transformer**

Performance	Deep Learning Model			
	CNN	BiLSTM	Hybrid CNN-BiLSTM	BERT
Accuracy	74%	85%	74%	<b>90%</b>
Precision	79%	88%	68%	<b>90%</b>
Recall	69%	82%	<b>94%</b>	91%
F1-Score	74%	85%	79%	<b>91%</b>
Macro Precision	74%	85%	78%	<b>90%</b>
Macro Recall	74%	85%	73%	<b>90%</b>
Macro F1-Score	74%	85%	72%	<b>90%</b>

Colab, which has Nvidia T4 GPU specifications and 12 GB RAM. This research uses the BERT model as the research baseline and is compared with deep learning algorithms such as CNN, BiLSTM, and Hybrid CNN-BiLSTM. A comparison of research can be seen in Table 7. From the results of the research done, it is evident that in general the BERT architecture used produces a classifier that is better than the other classifiers.

Based on Table 7, the difference between BERT performance and others is quite significant, for example on accuracy. BERT accuracy can reach 90% while CNN is only 74%. Where at least there is an increase in accuracy of up to 16%. Apart from accuracy, significant differences can also be seen in other metrics such as precision and f1-score. This proves that the BERT architecture is better in terms of natural language processing, especially for fake news detection. Another reason is that BERT can be better because of the pre-trained taken from a lot of data. Meanwhile, the deep learning model here only uses word embedding on the dataset used in the study, so the comparison of the amount of data also affects it. Research from Perez says that using a pre-trained model with a lot of data has an advantage over the embedding itself [17].

## 5 CONCLUSION

Problems regarding the spread of fake news occur in various countries including Indonesia. This research proves that the problem of detecting fake news in Indonesia can be solved using a deep learning model. This research shows that the proposed method produces a better model when compared to other models. BERT as a "state-of-the-art" model can outperform other models in various performance metrics such as accuracy, precision, and F1-score.

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