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Comparative study of predictive models for hoax and disinformation detection in indonesian news

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ABSTRACT

Along with the times, false information easily spreads, including in Indonesia. In Press Release No.485/HM/KOMINFO/12/2021, the Ministry of Communication and Information has cut off access to 565,449 negative content and published 1,773 clarifications on hoax and disinformation content. Research has been carried out regarding this matter, but it is necessary to classify fake news into disinformation and hoaxes. This study compares our proposed model, an ensemble of shallow learning predictive models, namely Random Forest, Passive Aggressive Classifier, and Cosine Similarity, and the deep learning model that uses BERT-Indo for classification. Both models are trained using equivalent datasets containing 8757 news, consisting of 3000 valid news, 3000 hoax news, and 2757 disinformation news. This news was obtained from websites such as CNN, Kompas, Detik, Kominfo, Temanggung Mediacenter, Hoaxdb Aceh, Turnback Hoax, and Antara, which were then cleaned from all unnecessary substances, such as punctuation marks, numbers, Unicode, stopwords, and suffixes using the Sastrawi library. At the benchmarking stage, the shallow learning model is evaluated to increase accuracy by applying ensemble learning combined with hard voting. This results in higher values, with an accuracy of 98.125%, precision of 98.2%, F-1 score of 98.1%, and recall of 98.1%, compared to the BERT-Indo model which only achieved 96.918% accuracy, 96.069% precision, 96.937% F-1 score, and 96.882% recall. Based on the accuracy value, the shallow learning model is superior to the deep learning model. This machine-learning model is expected to be used to combat the spread of hoaxes and disinformation in Indonesian news. Additionally, with this research, false news can be classified in more detail, both as hoaxes and disinformation.

1. Introduction

With the development of technology and digital media based on information and communication technology (ICT), news or conspiracy theories are easily spread [1]. This is indicated by the increasing number of sites that spread fake news. Meanwhile, news should provide independent, reliable, accurate, and comprehensive information for the public [2].

In Indonesia itself, the spread of false information is still common. In Press Release No.485/HM/KOMINFO/12/2021, the Ministry of Communication and Information has cut off access to 565,449 negative content and published 1,773 clarifications on hoax and disinformation content [3].

Wrong information will be very detrimental if it has an impact on many people. This misinformation can be in the form of hoaxes or disinformation

According to a 2018 report by the High Level Expert Group on Fake News and Online Disinformation of the European Commission, disinformation includes all forms of false, inaccurate, or misleading information that is intentionally designed, presented, and promoted to cause public harm or gain [4]. Disinformation refers to the distribution or dissemination of false, false, misleading or intentionally distorted information to mislead, deceive, or confuse the recipient. Lies then become the main persuasive element that takes advantage of the ambiguity of our language to encourage people to take certain actions. Misinformation given to the public ultimately determines how they act and spreads certain moral judgments to the people who read the disinformation [5].

Meanwhile, the hoax is news that contains false or inaccurate facts and is presented as valid facts [6]. The dissemination of hoax information usually has a dual purpose: to persuade or manipulate public opinion. The spread of hoaxes is also usually accompanied by fraud and even threats [7]. Recent reporting has also highlighted how powerful figures can exploit social media to manipulate individuals through targeted campaigns [6]. During election season, the main motive is to mislead readers and defame opponents. However, a group of people might share it for monetary gain [8].

The more hoaxes that are spread, the more we should care to find and delete them people. Thus, the role of the media in providing accurate and timely information to the public becomes more important [1]. Previously, several similar studies have used a machine learning approach to detect hoaxes using various machine learning models. This is because machine learning is able to make predictions based on existing historical data [9].

In addition, other studies use BERT in building predictive models. BERT, Bidirectional Encoder Representation from Transformers, is a transfer learning model designed to pre-train a deep representation of a left and right text [10]. BERT can be easily adapted to perform a classification simply by adding one additional classification layer so that we do not need to train a new model from scratch [11]. Just to note, using a transformer for social media sources [12] and news headlines is different.

In recent years, various studies have been carried out aimed at solving the problem of detecting false information. Especially during the Covid-19 pandemic, Bafadal et al. introduced how to map hoax messages [13]. Some of these studies use the features and models of Shallow Learning [6] as research conducted by Ula Munirul, Mulia Mahendra Alvanof, and Rahmat Triandi in 2020, which stated that the Random Forest algorithm is the best Shallow Learning algorithm compared to the Multilayer Perceptron, Naïve Bayes, and Support Vector Machine algorithms in news classification [14].

There are also studies that try to detect hoax news using more modern methods, such as deep learning, such as in the research conducted by Aisyah Awalina, Jibran Fawaid, Rifky Yunus Krisnabayu, and Novanto Yudistira in 2021. In this study, there were differences in BERT performance, with others being quite significant, for example, in accuracy. BERT accuracy can reach 90%, while CNN is only 74%, where there is at least an increase in accuracy of up to 16% [15].

In the same year, Lya Hulliyyatus Suadaa, Ibnu Santoso, and Amanda Tabitha Bulan Panjaitan made a comparison between the fine-tuned models on the original pre-trained BERT, multilingual pre-trained mBERT, and monolingual pre-trained BERT-Indo in classifying hoaxes in Indonesian. As a result, the fine-tuned BERT-Indo model trained on the Indonesian language corpus outperformed the original BERT and the uncased version of the multilingual BERT. However, the fine-tuned model on the cased version of mBERT trained with a larger corpus has the best performance [11].

However, the classification carried out in these studies only divides the news into two categories: hoax and valid. In fact, fake information or news can be disinformation or hoaxes [6]. Hence, in this study, we divided the news in the dataset into three labels: valid, hoax, and disinformation. This allows for more specific categorization of the news and prevents mixing between hoax and disinformation articles. This approach also enables the machine learning model to better identify and classify news articles. On the other hand, these studies only compare the level of accuracy between fellow Shallow Learning and Deep Learning as research by Sucheta et al. [16].

Therefore, we want to experiment to find out which model is better than our proposed model, which is an ensemble of shallow learning predictive models, namely Random Forest, Passive Aggressive Classifier, and Cosine Similarity, and the Deep Learning model, specifically BERT-Indo. By doing so, we aim to obtain a machine-learning model that can be used to combat the spread of hoaxes and disinformation in Indonesian news. The machine learning model obtained in this research can also be further developed in future studies.

2. Method

This research scheme is divided into several steps, as illustrated in Fig. 1: (1) Data Mining, (2) Data Preprocessing, (3) Data Modeling, (4) Building Machine Models, (5) Training Machine Models, (6) Benchmarking & Model Evaluation. This method also improves the Bharati MR et al. technique [17].

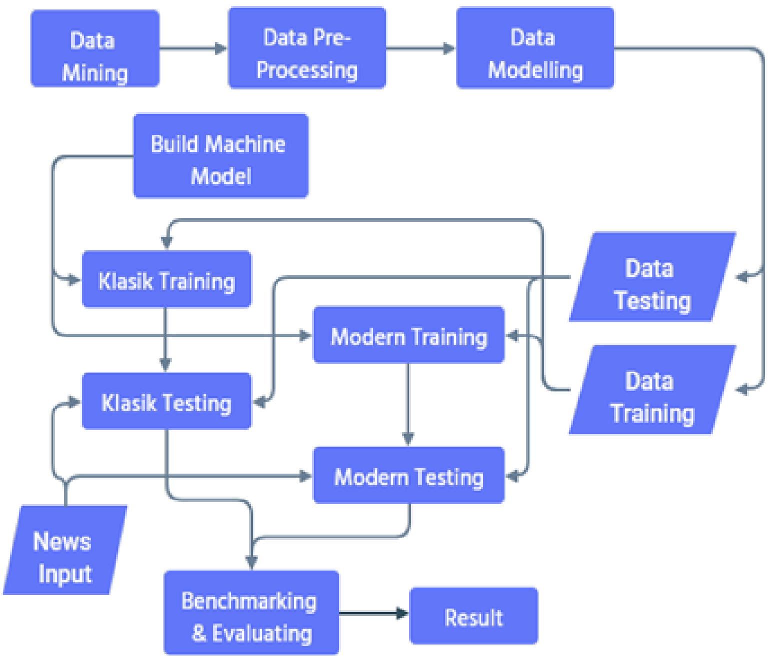

Fig. 1. Research Methodology

2.1. Data Mining

Data mining has a lot of techniques, as described by Changpetch et al. [18], from preparation to the set of data [19]. To create a dataset that will be used in this study, we conducted data mining on an Indonesian online news media portal. Data mining itself is a process to obtain knowledge from a data set [20]. The stages that we use in doing data mining can be seen in Fig. 2.

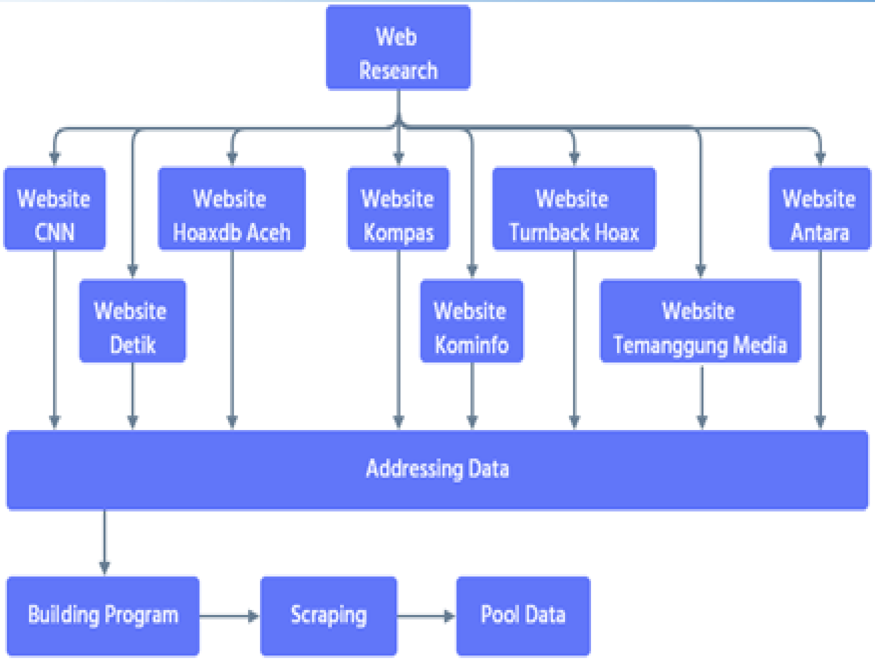

Fig. 2. Data mining methodology

Previously, we did research first to determine which news portal was appropriate and had accurate information. Finally, we chose CNN, Kompas, and Detik as valid news sources. These news portals are known and trusted in Indonesia. Meanwhile, we chose news portals owned by Kominfo, Temanggung Mediacenter, Hoaxdb Aceh, Turnback Hoax, and Antara as sources of hoax and disinformation. This is because these news portals present news that has been labeled as both hoax and disinformation.

Next, we address the data to determine the location of the data we want to extract from each of these websites. We use the inspect element feature for this process. Then, enter the desired data's address into the scrapping program. The scraping program that we compiled uses Python with the Scrapy library. The process of extracting information from a website is also known as web mining [21].

The scraping process was conducted between October and November 2021. The news articles were extracted from the websites mentioned in Fig. 2 without using specific keywords. This was done in order to gather all the news articles, resulting in a diverse dataset covering various topics. By doing so, it is expected to enhance the machine learning model's performance in predicting false information in real-world news.

After scraping on these websites, a total of 42855 news articles were obtained in the form of raw data, consisting of 30780 valid news articles, 9318 hoax news articles, and 2757 disinformation news articles. This raw data will then be forwarded to the data preprocessing stage for further processing.

2.2. Data Preprocessing

Preprocessing is the first step of sentiment analysis after the dataset is obtained. This process is used to clean and prepare the text for sentiment classification. This is because text written by users is usually in an unstructured state, where unstructured text usually contains a lot of distracting, unnecessary, or useless information, such as repetitive words, numbers, punctuation marks, HTML tags, URLs, scripts, advertisements, stopwords, abbreviations, emoticons, slang words, misspellings, shortcuts, and certain terminology [22]. Data preprocessing is shown in Fig. 3.

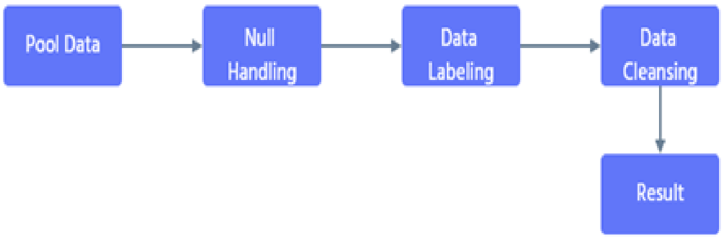

Fig. 3. Data Preprocessing methodology

As shown in Fig. 3, there are several stages of preprocessing that we carry out, which are as follows:

- Data Pools: Accommodates all raw data mining results in a file
- Null Handling: Remove NULL or NA from the dataset
- Data Labeling: Label the data with One Hot Encoding, where there are 3 labels, namely Hoax, Valid, and Disinformation
- Data Cleansing: Clean data from all unnecessary substances, such as punctuation marks, numbers, Unicode, stopwords, and suffixes. This process utilizes NLP with the Sastrawi library.

2.3. Data Modelling

When the data has gone through the preprocessing stage, the data is still in an unbalanced form, as can be seen in Fig. 4a. The data modeling stage aims to select the most suitable sample dataset to be able to make predictions with the highest accuracy. The preprocessed data, originally in the form of text, was converted into numeric format by calculating the Term Frequency and Inverse Document Frequency (TF-IDF). Then, the data in each category was shuffled/randomized, and data balancing was performed for hoax, valid, and disinformation news. The best samples were selected based on the highest TF-IDF values.

After that, the data will look like in Fig. 4b. There was a downscaling so that the number of data that was previously 42855 news became 8757 news, consisting of 3000 valid news, 3000 hoax news, and 2757 disinformation news. This data will later be divided into train and test data, which will be used in the training and testing stages.

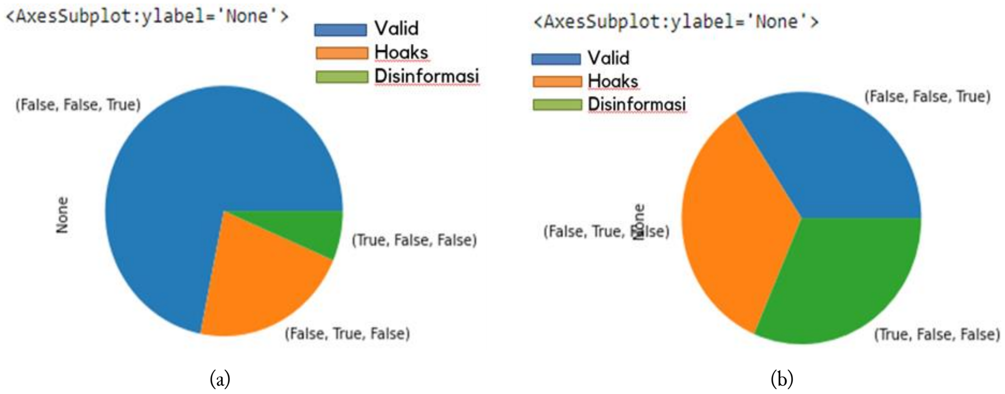

Fig. 4. Comparison of data before and after being modeled

2.4. Building Machine Learning Models

In the experiments we conducted, we applied the experimental method. So, the model parameters' values were determined based on the experiments by observing the best results and avoiding excessively long running times. The purpose of this experiment is to find out and test whether the proposed machine learning model can outperform the BERT-Indo model in classifying Indonesian news.

2.5. Shallow Learning

In this case, the Shallow Learning model that we use are: (1) Random Forest, (2) Passive Aggressive Classifier, (3) Cosine Similarity. Using the hard voting method, the proposed model will combine these three models in an ensemble model.

2.5.1. Random Forest (RF)

Random Forest is one of the machine learning algorithms used for classification and regression analysis. Random Forest is composed of decision trees. A forest consists of several trees. Random Forest forms a decision tree on an arbitrarily selected data sample, obtains a predicted output from each tree, and selects the optimal result using a voting mechanism. This is the application of the ensemble method, which aims to reduce overfitting by averaging the predictions so that the results are much better than those of a single decision tree [8]. It can handle both categorical and numerical data and provides feature importance rankings. However, fine-tuning hyperparameters can be computationally expensive, less interpretable, and challenging. The configuration of the Random Forest model that we used in this study can be seen in Table 1.

Table 1. Random Forest architecture

Parameter	Value
n_estimators	1000
max_depth	None
n_jobs	-1

2.5.2. Passive Aggressive Classifier (PAC)

The Passive Aggressive Classifier Algorithm is a set of algorithms used for comprehensive learning. This algorithm is very similar to the Multilayer Perceptron, except for its learning speed. However, unlike Perceptron, the passive-aggressive algorithm consists of regularizing the C variable [23]. PAC is suitable for real-time data, with minimal memory requirements and the ability to handle high-dimensional data. It is relatively easy to implement but may be sensitive to data order and struggle with imbalanced datasets. The parameters we use are as shown in Table 2.

Table 2. Passive Aggressive Classifier architecture

Parameter	Value
max_iter	1000

2.5.3. Cosine Similarity (CS)

Cosine Similarity is a measurement that calculates the similarity value between two or more vectors. Cosine Similarity is used to calculate the cosine value between the document vector and the required input vector. The smaller the output produced, the higher the level of document similarity that occurs [24]. CS is a simple and efficient measure for comparing vector similarity, commonly used in text mining.

It is computationally efficient and insensitive to vector magnitude but lacks semantic meaning and may not be suitable for all scenarios. The formula for Cosine Similarity can be seen in Formula 1 [25].

$$Cos\ \alpha = \frac{AB}{|A||B|} = \frac{\sum_{i=1}^{n} Ai \times Bi}{\sqrt{\sum_{i=1}^{n}(Ai)^2 \times \sum_{i=1}^{n}(Bi)^2}} \quad (1)$$

2.6. Deep Learning (BERT-Indo)

Meanwhile, we use transfer learning from BERT-Indo for deep learning machine models. BERT applies a transformer architecture, where the focus method used is Attention. Attention is a method to determine a data sequence's main focus or context. For example, instead of just translating between languages, the encoder will also write down keywords/important words. Attention is also a function used to map queries using a key-value format, all of which output is in vector form [15]. BERT-Indo can captures contextual information, handles complex language structures, and achieves state-of-the-art performance. However, it requires high computational resources, has a large memory footprint, and longer training and inference times. Fine-tuning also requires task-specific labeled data.

Furthermore, the architectural model that we applied for BERT-Indo in this study can be seen in Table 3. In this case, we use a pre-trained model from BERT-Indo called 'indoor-large-p1' with the Adam optimizer and the Cuda device.

Table 3. BERT-Indo architecture

Hyperparameter	Value
Loss function	Categorical-crossentropy
Learning rate	3e-6
Optimizer	Adam
Device	Cuda
Number of epochs	2
Batch size	4
Max sequence length	128

2.7. Train Machine Learning Models

In conducting this research, we used media in the form of a Google Colab free version with specifications such as GPU NVIDIA K80s, T4s, P4s, and P100s, and 13GB of RAM. Google Colab is an incredible online browser-based platform that allows us to train our machine models [26]. As described by David et al. [27], we built and modified to train shallow learning models (RF, PAC, CS); the previously modeled dataset will be split with a proportion of 3% test data and 97% train data. Meanwhile, the BERT-Indo model will be trained with 90% of the dataset, while 7% and 3% of the dataset will be used for the validation set and test set. In addition, both models will also be tested with news input that is not included in the dataset.

2.8. Benchmarking & Model Evaluation

Shallow learning models will be evaluated based on the quantity of True Positive, False Positive, True Negative, and False Negative, as well as improving the algorithm's accuracy with several mechanisms, such as data modeling and multiple algorithms (RF, PAC, CS). After that, the BERT-Indo model will be compared with the results from the shallow learning model that has been obtained. So, we can see the difference in the accuracy of the two models.

3. Results and Discussion

We conducted extensive training and analysis on both the shallow learning models (Random Forest, Passive Aggressive Classifier, and Cosine Similarity) and the deep learning model (BERT-Indo) to compare their performance in the same environment. In order to ensure a fair evaluation, we used the same dataset for training and testing purposes.

Based on Fig. 5, Random Forest achieved higher average results than PAC when trained using a small sample of data, accounting for 10% of the randomly selected 8757 from the datasets. Random Forest has a precision of 96.9%, recall of 88.1%, F1-score of 91.8%, and accuracy of 88.1%, with an average of 91.225%. Passive Aggressive Classifier has a precision of 90.6%, recall of 90.5%, F1-score of 90.5%, and accuracy of 90.5%, with an average of 90.525%. Meanwhile, cosine similarity is not a machine-learning algorithm by itself. Instead, it is a mathematical similarity metric used in various machine learning tasks, particularly in natural language processing and information retrieval. Therefore, we proceeded to compare Random Forest with the ensemble model and BERT-Indo.

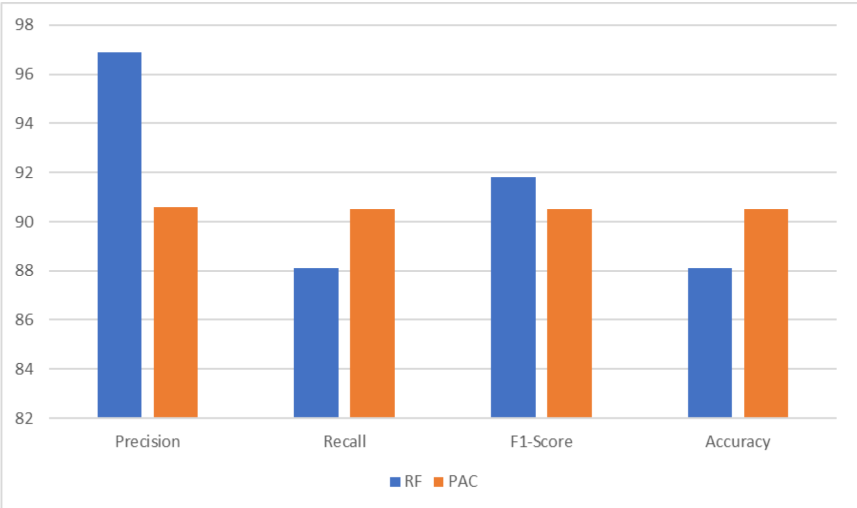

Fig. 5. Comparison of RF and PAC with small data train

Before that, we aim to create a suitable dataset for machine learning. In other words, we will choose appropriate preprocessing methods to obtain the maximum accuracy or results from the dataset. Therefore, the authors have created five different preprocessing method schemes, as shown in Table 4. These methods will be tested using Random Forest, referring to Fig. 5.

Table 4. Preprocessing Scheme

Methods	Description
Sentence 1	Tokenized word with removed 'special char', 'punctuation', 'single char', 'number', and 'multiple whitespace'
Sentence 2	Tokenized word with removed 'special char', 'punctuation', 'single char', 'number', 'multiple whitespace', and normalized by kamusalay
Sentence 3	Tokenized word with removed 'special char', 'punctuation', 'single char', 'number', and 'multiple whitespace', 'stopwords', and normalized by kamusalay
Sentence 4	Tokenized word with removed 'special char', 'punctuation', 'single char', 'number', and 'multiple whitespace', 'stopwords', normalized by kamusalay and, stemmed by Sastrawi

Based on Table 5, it can be seen that the Sentence 4 method obtained the highest values in terms of accuracy, F1-score, recall, and precision. For this reason, we decided to apply Sentence 4 method in data preprocessing. After performing data preprocessing, the dataset will be modeled by transforming it into a numeric format using TF-IDF calculations. Next, the data in each category underwent shuffling/randomization, and a data balancing process was conducted for hoax, valid, and disinformation news. The best samples were selected based on the highest TF-IDF values consisting of 3000 hoax news, 3000 valid news, and 2757 disinformation news. So, the modelled dataset will contain a total of 8757 news.

Table 5. Comparison of Random Forest's Result Between Methods

Result	Sentence 1	Sentence 2	Sentence 3	Sentence 4
Precision	0.986	0.986	0.986	0.987
Accuracy	0.915	0.916	0.918	0.921
Recall	0.915	0.916	0.918	0.921
F1-Score	0.947	0.948	0.949	0.951

The training results of the shallow learning models are shown in Table 6. The training was conducted using different approaches: (1) Random Forest without Data Modelling, (2) Random Forest with Data Modelling, and (3) Ensemble (RF, PAC, CS) with Data Modelling. This study did not compare each shallow learning algorithm but focused on the Random Forest and the Ensemble (RF, PAC, CS). However, combining all three algorithms in the ensemble model yielded even higher accuracy.

Table 6. Comparison of Shallow Learning Model and Deep Learning Model

Model	Akurasi	Presisi	F-1	Recall
Random Forest without Modelling Data	92.2	97.9	94.7	92.2
Random Forest with Modelling Data	94.3	**99.2**	96.5	94.3
Ensembel (RF, PAC, CS) with Modelling Data	**98.1**	98.2	**98.1**	**98.1**
BERT-Indo	96.918	96.069	96.937	96.882

Accuracy, precision, F-1 score, and recall values were obtained by calculating True Positive, False Positive, True Negative, and False Negative from the predictions. The ensemble model of Random Forest, Passive Aggressive Classifier, and Cosine Similarity achieved the highest average accuracy score of 98.125%. Furthermore, applying data modeling techniques to the dataset resulted in an average increase of 2.275% in accuracy across all models. Therefore, we selected the ensemble model (RF, PAC, CS) for comparison with the BERT-Indo model. Detailed prediction results are shown in Fig. 6.

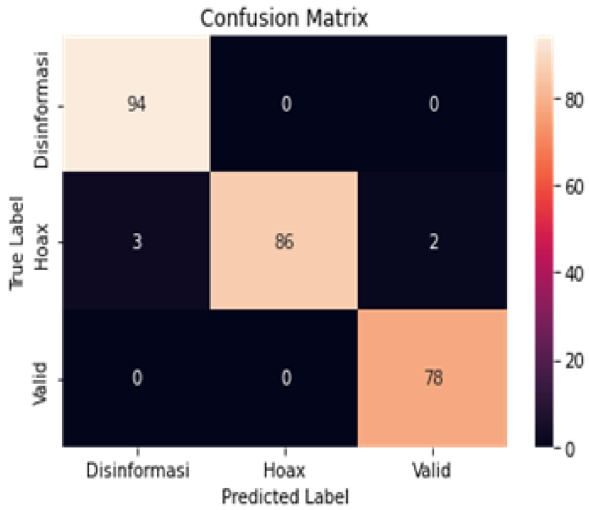

Fig. 6. Confusion Matrix Ensemble Model (RF, PAC, CS) with Modeling Data

The results of the BERT-Indo model can be seen in Table 6. Fine-tuning the BERT-Indo model with the use of a modeled dataset enabled the model to achieve an accuracy of 96.918%. Additionally, precision, recall, and F-1 score values were recorded at 96.069%, 96.882%, and 96.937% respectively. The advantage of The BERT-Indo model is that it provides information on the prediction rate for the given input, making the prediction results more informative and reliable. In this case, we included a valid news fragment from the Detik website [28], a hoax news fragment from the Antara website [29], and a disinformation news fragment from the Kominfo website [30]. The model successfully predicted the news as valid with a valid rate of 42.145%, a hoax rate of 87.674%, and a disinformation rate 99.584%.

Based on the data in Table 6, it is evident that the ensemble model achieved the highest accuracy rate at 98.1%. This indicates that the ensemble model produced the highest number of correct predictions (TP+TN) compared to other models and scenarios. Additionally, the ensemble model exhibited the highest F-1 score and recall percentages. In other words, the ensemble model accurately predicted the TP data with a high average ratio compared to the total true positive data (TP+FN) and total positive predictions (TP+FP). On the other hand, the Random Forest with data modeling showed the highest precision of 99.2%. A high precision value indicates that the model had the highest ratio of correct positive predictions (TP) compared to the total positive predictions (TP+FP). However, the ensemble model cannot provide information about the prediction rate as the BERT-Indo model does. Nonetheless, the testing results with news fragments from Detik [28], Antara [29], and Kominfo [30] can still be accurately predicted by the ensemble model.

Based on these results, the ensemble model demonstrated higher accuracy, F-1 score, and recall compared to the BERT-Indo model. This could be due to the dataset used in the training process. The Bert-Indo GitHub repository [31] states that the Bert-Indo model has been trained with datasets from Wikipedia, Tempo, Kompas, Liputan6, and the Indonesian Web Corpus, with the latest data taken in 2017. Looking at the data sources, the Bert-Indo model is not familiar with the types of hoaxes and disinformation news present in Indonesian online news media. Based on these results, the ensemble model can be applied to predict whether an Indonesian news article is valid, a hoax, or disinformation. This approach can help reduce the harm caused by hoaxes and disinformation, which aim to mislead, deceive, or confuse readers.

4. Conclusion

From our research, it can be concluded that the shallow learning model is still relevant and promising to be used in detecting false information, both hoaxes and disinformation, in Indonesian online news. With some special treatment, the predictions generated by the shallow learning model can outperform the deep learning model. In this case, the shallow learning ensemble model (RF, PAC, and CS) has an accuracy of 98.1%, while the BERT-Indo model is only 96.918%. It should be noted that the configuration of the shallow learning and deep learning models also influences this result. Different model architectures will affect the performance of the model. In addition, the dataset used in the training process will also affect the predictive ability. It is proven by the increase in each accuracy value by an average of 2.275% when the shallow learning model is trained using datasets that have passed the data modeling process. Based on these findings, our proposed model can be utilized to counter the dissemination of hoaxes and disinformation in Indonesian news.

Furthermore, this study enables a more comprehensive classification of false news, distinguishing between hoaxes and disinformation. Further research can be carried out using new datasets or implementing different model layouts and architectures for comparison. This study also only used a single dataset and did not consider the influence of external factors such as social media algorithms, user behavior, or cultural norms.

Declarations

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