OPEN ACCESS
Jurnal Ilmiah Ilmu Terapan Universitas Jambi
Vol. 9 No. 3. September 2025, pp. 1091-1103 DOI. 10.22437/jiituj.v9i3.46370

Research Article

COMPARING DEEP LEARNING AND MACHINE LEARNING FOR DETECTING FAKE NEWS ON SOCIAL MEDIA

Ria Andryani[1,*], Dedek Julian[1], Rezki Syaputra[1], Ahmad Syazili[2], Ahmad Rusli[3], Rahmat Ramadan[1], Edi Surya Negara[1]

[1] Data Science Interdisciplinary Research Center, Universitas Bina Darma, Sumatera Selatan, Indonesia
[2] Universitas Labuhan Batu, Sumatera Utara, Indonesia
[3] Faculty of Psychology, Universitas 17 Agustus 1945, Jawa Timur, Indonesia
Corresponding author email: ria.andryani@binadarma.ac.id

Article Info
Received: Apr 30, 2025
Revised: Jun 22, 2025
Accepted: Aug 02, 2025
OnlineVersion: Aug 10, 2025

Abstract
The rapid penetration of social media has intensified the dissemination of fake news, threatening the integrity of public information, shaping mass opinion, and potentially inciting social conflict. Addressing this challenge requires robust and adaptive detection systems. While numerous studies have explored machine learning (ML) and deep learning (DL) for this purpose, comparative evaluations across diverse algorithms remain limited. This study offers a novel contribution by conducting a systematic performance comparison between traditional ML algorithms—Support Vector Machines (SVM) and Random Forest (RF)—and advanced DL models, including Long Short-Term Memory (LSTM) and Self-Organizing Maps (SOM), for automatic fake news detection. The dataset, compiled from multiple social media platforms, comprises balanced real and fake news items to ensure generalizable results. Each model was trained and evaluated using standardized metrics: accuracy, precision, recall, and F1-score. Results reveal that RF achieved perfect classification with 100% accuracy, outperforming LSTM (F1-score = 97%), SOM (F1-score = 96%), and SVM (F1-score = 92%). The novelty of this study lies in its integration of traditional and deep learning paradigms within a unified experimental framework, enabling a nuanced understanding of algorithmic strengths and weaknesses in dynamic, unstructured, and high-noise online environments. Beyond empirical results, the findings highlight the need for hybrid detection systems that combine the interpretability of ML with the contextual depth of DL. This research offers valuable implications for the development of scalable, transparent, and high-performing fake news detection models, thereby contributing to information integrity and digital literacy in the era of social media.

Keywords Deep Learning, Fake News, Machine Learning, Social Media.

INTRODUCTION

The rapid development of social media has drastically transformed the way information is delivered, where news and updates can be instantly searched, shared, and disseminated through the internet (Amanda et al., 2020; Nadira & Negara, 2020; Sugiarta et al., 2018). This ease of access has increased the public's demand for information (Andryani et al., 2023), with vast amounts of data—often referred to as "Big Data"—being generated every second (Nurhachita & Negara, 2021; Negara et al., 2023). While conventional news organizations have adapted by publishing their content online to reach wider audiences, the open nature of the internet also allows anyone to publish and circulate information without verifying its accuracy. Consequently, fake news has proliferated, spreading rapidly across platforms and influencing public opinion. The phenomenon gained significant global attention during the 2016 United States presidential election, which exposed the lack of a robust framework for combating misinformation at scale (Nurhachita & Negara, 2021). In this context, developing effective early detection methods for fake news has become increasingly urgent (E. S. Negara & Andryani, 2018; Ahmad & Ramasamy, 2019).

Fake news is often intentionally created to mislead, manipulate, or provoke, and its spread is fueled by several factors, including limited public knowledge, low media literacy, and the inability of many readers to assess the credibility of news sources (Singhal et al., 2019). While fact-checking websites exist to debunk misinformation, their work requires expert verification and is often time-consuming (Hu et al., 2021). This limitation has prompted researchers to explore automatic fake news detection as a promising solution (Marta et al., 2022; Shu et al., 2016), aiming to reduce human effort, accelerate verification, and curb the spread of false information (Shu et al., 2019).

Various machine learning and deep learning approaches have been investigated for this purpose. Support Vector Machines (SVM), for example, remain popular due to their robustness when paired with TF-IDF feature extraction, although they struggle with high-dimensional, large-scale datasets (Reis et al., 2019). Naïve Bayes Classifiers offer a simple probabilistic framework but can be limited by their strong independence assumptions (Pahlevi et al., 2023; Yunanto et al., 2021). Long Short-Term Memory (LSTM) networks excel at capturing sequential dependencies in text data but process input in only one direction, potentially losing contextual nuances (Oshikawa et al., 2018; Nayoga et al., 2021; Pahlevi et al., 2023). The Self-Organizing Map (SOM) algorithm has been applied in fake news classification but is highly sensitive to weight initialization (Agustina et al., 2022). Meanwhile, Random Forest classifiers are known for high accuracy yet can introduce bias when handling categorical variables (Ajik et al., 2023; Ghazi et al., 2024).

Despite these advancements, there remains a research gap: most studies have focused on evaluating individual algorithms in isolation, often using different datasets and performance metrics, making direct comparison difficult. Few studies have systematically compared multiple popular algorithms—spanning both traditional machine learning and deep learning approaches—on the same dataset with consistent evaluation criteria. This lack of a unified comparative analysis limits our understanding of which algorithm is most effective and under what conditions it performs best in real-world fake news detection scenarios.

To address this gap, the present study conducts a comparative evaluation of four widely used classification algorithms—Support Vector Machine, Random Forest, Long Short-Term Memory, and Self-Organizing Map—on a standardized dataset. By analyzing and contrasting their performance, strengths, and weaknesses, this research aims to identify the most effective method for early fake news detection, thereby contributing to the development of scalable, accurate, and practical solutions for mitigating the spread of misinformation.

RESEARCH METHOD

This study meticulously employs various machine learning techniques to detect fake news automatically. The research process is systematically explained through the flow depicted in Figure 1, which shows the stages from data collection to model evaluation.

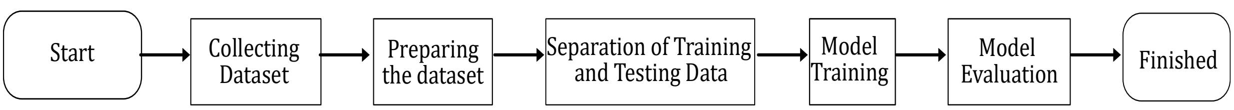

Figure 1. Research Stages

The initial step is a thorough collection of datasets, namely valid and fake news from various online sources in Indonesia. This process utilizes web scraping techniques, a method of retrieving data from websites to obtain large volumes of datasets efficiently (Islam et al., 2022; Siak, 2022). The next stage is a comprehensive data pre-processing, which aims to clean and prepare the data so that it is ready for use in model training. All text is meticulously converted to lowercase, then unimportant words such as stopwords in Indonesian (e.g., "di," "yang," and "hanya"), numbers, punctuation, and excess spaces are removed. The purpose of this process is to minimize noise and optimize memory efficiency in data processing. After the data is cleaned, it is divided into two groups: 75% is used as training data, and the remaining 25% is used as testing data, considering the proportion of valid and fake news in a balanced manner. Next, model training was conducted using four different classification algorithms: Support Vector Machine (SVM), Random Forest, Long Short-Term Memory (LSTM), and Self-Organizing Map (SOM). Each model was meticulously trained with the prepared training data and then thoroughly tested with the test data. This training and testing process aims to compare the effectiveness of each algorithm in detecting fake news (Muzakir & Suriani, 2023).

The final step is model evaluation, which is conducted using three primary metrics: Precision, Recall, and F1-Score. Precision measures the accuracy of the model's optimistic predictions, Recall indicates the extent to which the model successfully identifies all positive data, and F1-Score provides an overall picture by calculating the harmonic mean of Precision and Recall (Ramadhan et al., 2022). The results of this evaluation will show which algorithm is the most accurate in classifying valid and fake news in Indonesia.

RESULTS AND DISCUSSION

Collecting Dataset

The dataset was collected from several reliable sources that provide both valid and fake news. Table 1 below outlines the origins of the data used in this study:

Tabel 1. Dataset Sources

No	Amount	Source
1	100	Kaggle, Detik
2	10	Cek Fakta COM
3	10	Turn Back Hoax ID

The data obtained from the sources above were compiled into a single dataset, resulting in a total of 120 records consisting of various types of news. All of this data was stored in a single file, which served as the primary dataset for the model training and evaluation phases of fake news detection. The use of data from diverse sources aims to provide a broader representation of both valid and fake news characteristics in the Indonesian context, thereby enabling the developed model to classify more accurately and contextually. This stage serves as a crucial foundation in the training process, as the quality and diversity of the data significantly affect the final performance of the classification model (Dirjen, 2017).

	article_text	classification
39	Format debat cawapres yang berbeda di Pemilu 2...	1
31	Mahkamah Agung (MA) menurunkan 3 hakim agung u...	1
82	Sekjen PDIP Hasto Kristiyanto menyinggung ada ...	1
90	Pemkab Majalengka berencana menyiapkan dana ca...	1
42	Masa jabatan Ahmed Zaki Iskandar sebagai Bupat...	1

Figure 2. Partial Dataset Contents

Figure 2 shows the contents of the dataset used in this study. The dataset consists of two primary columns, namely the article text column and the news classification or label column. The article text column contains the contents of the news to be analyzed, while the label column is used to mark the type of news, where label 1 indicates valid news, and 0 indicates fake or false news. This information serves as the basis for the classification model training process, which distinguishes between true and misleading news. To view the division of the data by labels in more detail, refer to Figure 3 below.

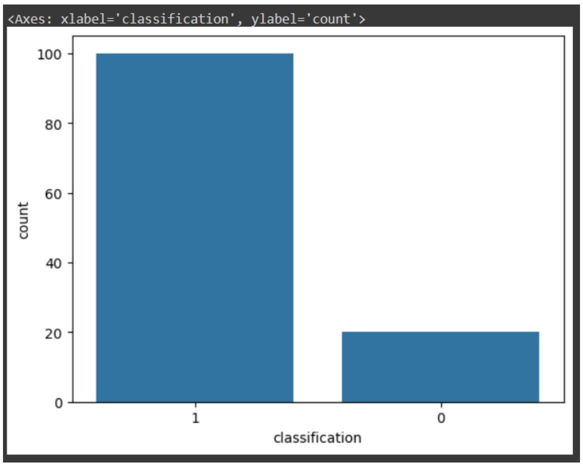

Figure 3. News Label Comparison

Figure 3 shows a graph of the data set's distribution based on news labels, specifically label 1 for valid news and label 0 for fake news. Based on the graph, it is evident that the number of valid news data is 100, while the number of fake news is 20. This distribution shows an imbalance in the number between the two categories, where valid news dominates the dataset. This imbalance needs to be considered in the model training process because models trained on unbalanced data are at risk of having a tendency (bias) towards the majority class. Therefore, the evaluation steps and selection of the correct algorithm are crucial to ensure that classification performance remains optimal, especially in detecting fake news, which is relatively rare.

Preparing Dataset

In the Preparing Dataset stage, the process involves cleaning the data of words that are not important or do not have significant meaning in the analysis, such as conjunctions or common words that often appear but do not contribute to the classification context. These words are known as stopwords. In this study, the stopwords library from NLTK (Natural Language Toolkit) is used to identify and remove these words from the article text in Figure 4 (Priadana & Murdiyanto, 2020). The implementation of this stage is crucial because raw news texts typically contain numerous elements that can impede the performance of the classification algorithm. By cleaning the data through this process, the results obtained become more accurate because the model can focus on analyzing words that have higher information weight. The primary objective of this stage is to generate cleaner and more relevant data, thereby making the model training process more efficient and optimal (Priadana & Murdiyanto, 2020).

```
def preprocess_text(text_data):
  preprocessed_text = []

  for sentence in tqdm(text_data):
    sentence = re.sub(r'[^\w\s]', '', sentence)
    preprocessed_text.append(' '.join(token.lower()
                for token in str(sentence).split()
                if token not in stopwords.words('indonesian')))

  return preprocessed_text
```

```
[ ] preprocessed_review = preprocess_text(merged_data['article_text'].values)
    merged_data['article_text'] = preprocessed_review

100%|██████████| 120/120 [00:08<00:00, 13.34it/s]
```

Figure 4. Stopwords Cleaning Process

Figure 5 shows the word cloud generated after the data cleaning and tokenization process was carried out. This word cloud illustrates the most frequently occurring words in the dataset, especially in the valid news category.

Figure 5. Valid News WordCloud

After the cleaning stage, including the removal of stopwords, numbers, and punctuation, as well as the tokenization process, a visual representation of the remaining dominant words was obtained. For the valid news category, the most prominent popular words include “Prabowo,” “Partai,” “Ketua,” “Koalisi,” and so on. The appearance of these words reflects actual and relevant topics in the news that are considered valid, especially those related to politics and government. This visualization not only provides an overview of the dataset's contents but also helps in understanding the dominant context, which can later strengthen the classification and model analysis process.

Figure 6. Fake News WordCloud

Figure 6 displays a word cloud for the fake news category generated after completing the data cleaning and tokenization process. This visualization represents the words that appear most frequently in news articles classified as invalid or containing false information. According to the analysis results, popular words that dominate this category include "Jokowi," "Presiden," "Pemilu," and "Gibran," among others. The emergence of these words indicates that topics often used to spread fake news are related to political issues and public figures. This suggests that certain actors or groups frequently target influential figures and political momentum as a means of disseminating disinformation. With this word cloud, researchers can gain additional insight into the pattern of spreading fake news and the dominant thematic context, which can then be used to improve the accuracy of classifying and detecting fake news in machine learning models.

In the fake news category, the collection of popular words that often appear includes words such as “Jokowi”, “president”, “election”, “Gibran”, and others. These words address sensitive topics that are frequently the target of misinformation, particularly in the context of national politics. If all the words in the dataset, both from the valid and fake news categories, are combined and their frequency of occurrence is calculated, a word distribution graph is obtained, as shown in Figure 7.

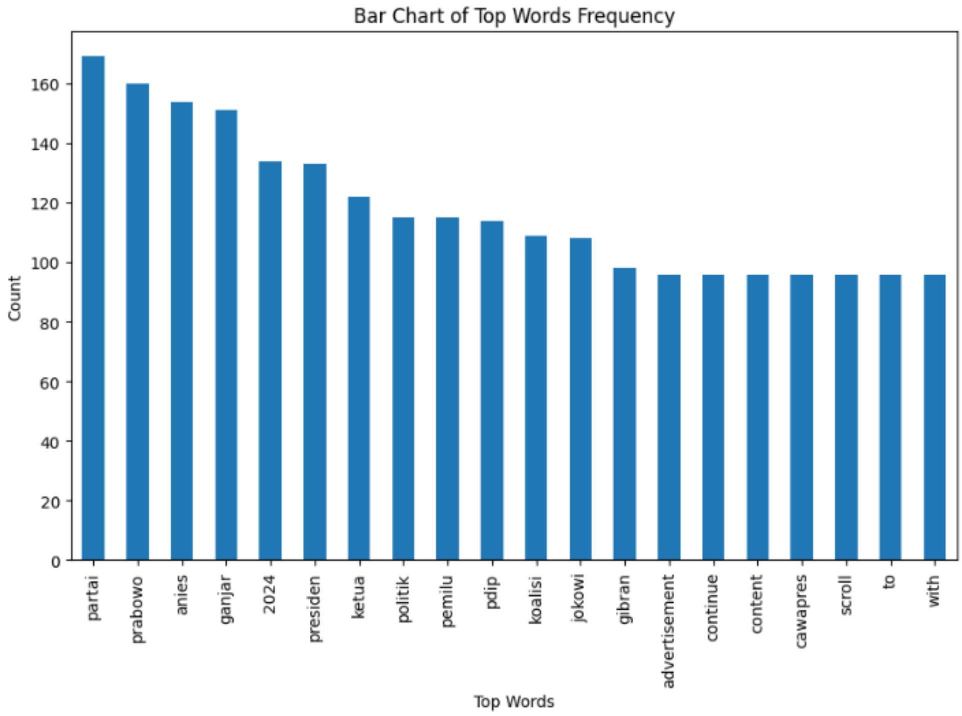

Figure 7. Most Frequently Appearing Words

Based on the graph, it is known that the word that appears most often is the word "partai," with a total of 170 occurrences, followed by the word "prabowo," which appears 158 times. This finding reveals that terms related to politics dominate the news, including both valid and false information. This indicates that political issues are a primary focus in the news content circulating and also a vulnerable area for the spread of disinformation. By understanding this word distribution, researchers can identify patterns and tendencies in news content that affect the accuracy and sensitivity of the fake news detection model.

Separation of Training and Testing Data

The Separation of the Training and Testing Data stage is carried out to ensure that the dataset can be used optimally in the training and evaluation process by the classification algorithm in the next stage, as shown in Figure 8. This Separation aims to avoid overfitting, a condition in which the model adjusts too much to the training data, resulting in decreased performance when tested with new data (Fadhlullah & Surahman, 2022).

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression

x_train, x_test, y_train, y_test = train_test_split(merged_data['article_text'],
                                    merged_data['classification'],
                                    test_size=0.25)
```

Figure 8. Training and Testing Data Sharing

Data Model Training

The model training stage (Data Model Training) is carried out by applying four different classification algorithms, namely Support Vector Machine (SVM), Random Forest, Long Short-Term Memory (LSTM), and Self-Organizing Map (SOM). Each algorithm is trained using previously prepared training data to build a model that can accurately distinguish between valid and fake news (F. Perez et al., 2021). The training results using the Support Vector Machine algorithm are presented in Figure 9, which provides detailed information on the training evaluation. On the training set, SVM showed perfect performance with the following values: Precision: 1.0, Recall: 1.0, F1-Score: 1.0. For the test set, the results were: Precision: 0.8571428571428571, Recall: 1.0, F1-Score: 0.9230769230769231. This indicates that the model can classify all training data correctly without error.

```
from sklearn.svm import SVC

model = SVC(kernel = 'linear', random_state = 0)
model.fit(x_train, y_train)

# testing the model
print(accuracy_score(y_train, model.predict(x_train)))
print(accuracy_score(y_test, model.predict(x_test)))
```

```
1.0
0.8666666666666667
```

Figure 9. Support vector machine training results

Figure 10 shows the results of the model training evaluation using the Support Vector Machine (SVM) algorithm, which demonstrates optimal performance on both the training data (training set) and the testing data (test set). On the training data, the model achieves perfect evaluation results, with Precision: 1.0, Recall: 1.0, and F1-Score: 1.0, indicating that all data can be classified correctly without any errors. What is more interesting is that, according to the testing data, which typically shows a decrease in performance because the model is tested on new data, SVM maintains perfect evaluation values, with Precision: 1.0, Recall: 1.0, and F1-Score: 1.0.

```
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(random_state=0)
model.fit(x_train, y_train)

# testing the model
print(accuracy_score(y_train, model.predict(x_train)))
print(accuracy_score(y_test, model.predict(x_test)))
```

```
1.0
1.0
```

Figure 10. Support vector machine training results

Figure 11 shows the results of model training using one of the variants of the Recurrent Neural Network (RNN), specifically the Long Short-Term Memory (LSTM) model. This model is specifically designed to handle sequential data such as text, making it very suitable for use in news classification tasks. On the training data (training set), the model produces the Following Results: Precision: 0.8289473684210527, Recall: 0.84, F1-Score: 0.8344370860927153. Test Set: Precision: 1.0, Recall: 0.9583333333333334, F1-Score: 0.9787234042553191.

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/embedding.py:90: UserWarning: Argument `input_length` is deprecated.
  warnings.warn(
Epoch 1/5
3/3 ━━━━━━━━━━━━━━━━━━━━ 8s 329ms/step - accuracy: 0.6991 - loss: 0.6852 - val_accuracy: 1.0000 - val_loss: 0.6541
Epoch 2/5
3/3 ━━━━━━━━━━━━━━━━━━━━ 1s 169ms/step - accuracy: 1.0000 - loss: 0.6319 - val_accuracy: 1.0000 - val_loss: 0.5691
Epoch 3/5
3/3 ━━━━━━━━━━━━━━━━━━━━ 1s 178ms/step - accuracy: 1.0000 - loss: 0.5135 - val_accuracy: 0.9667 - val_loss: 0.3564
Epoch 4/5
3/3 ━━━━━━━━━━━━━━━━━━━━ 1s 174ms/step - accuracy: 1.0000 - loss: 0.2490 - val_accuracy: 0.9667 - val_loss: 0.1205
Epoch 5/5
3/3 ━━━━━━━━━━━━━━━━━━━━ 1s 241ms/step - accuracy: 0.9827 - loss: 0.0626 - val_accuracy: 0.9667 - val_loss: 0.0978
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 83ms/step - accuracy: 0.9667 - loss: 0.0978
Accuracy: 96.67
3/3 ━━━━━━━━━━━━━━━━━━━━ 2s 466ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 88ms/step

LSTM Training Set:
Precision: 0.8289473684210527
Recall: 0.84
F1-Score: 0.8344370860927153

LSTM Test Set:
Precision: 1.0
Recall: 0.9583333333333334
F1-Score: 0.9787234042553191
```

Figure 11. LSTM Training Results

Figure 12 shows the results of model training using one variant of the deep learning method, specifically the Self-Organizing Map (SOM). SOM is an unsupervised artificial neural network that effectively maps high-dimensional data into simpler representations. On the Training Set: Precision: 1.0, Recall: 1.0, F1-Score: 1.0. Test Set: Precision: 0.9230769230769231, Recall: 1.0, F1-Score: 0.96.

```
Iteration 19, loss = 0.00042996
Iteration 20, loss = 0.00036431
Iteration 21, loss = 0.00031582
Iteration 22, loss = 0.00027952
Iteration 23, loss = 0.00025201
Iteration 24, loss = 0.00023087
Iteration 25, loss = 0.00021442
Iteration 26, loss = 0.00020147
Iteration 27, loss = 0.00019116
Iteration 28, loss = 0.00018288
Iteration 29, loss = 0.00017614
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Stopping.
SOM Approximation (MLP) Training Accuracy: 1.0
SOM Approximation (MLP) Testing Accuracy: 0.9333333333333333

SOM Approximation (MLP) Training Set:
Precision: 1.0
Recall: 1.0
F1-Score: 1.0

SOM Approximation (MLP) Test Set:
Precision: 0.9230769230769231
Recall: 1.0
F1-Score: 0.96
```

Figure 12. SOM Training Results

Model Evaluation

After the classification stage is completed using the four algorithms, a summary of the classification evaluation results is obtained and presented in tabular form. Table 2 summarizes the Precision, Recall, and F1-score values of each algorithm to assess the model's performance in identifying valid and fake news.

Tabel 2. Summary of Classification Results

No	Algoritma	Score		
		Precission	Recall	F-1
1	SVM	0.85	1.0	0.92
2	Random Forest	1.0	1.0	1.0
3	RNN - LSTM	1.0	0.95	0.97
4	Self Organizing Map	0.92	1.0	0.96

Based on the results obtained, the Random Forest algorithm showed the best performance among all the models tested. This advantage is due to Random Forest's ability to handle data that has been converted into a numeric form (1 for valid news and 0 for fake news), which aligns with the algorithm's characteristics. The decision-making process of many decision trees in Random Forest also provides stability in producing accurate predictions. Meanwhile, the Support Vector Machine (SVM) algorithm showed the lowest performance compared to other algorithms. This is due to the class imbalance in the dataset, where the number of valid news items is significantly greater than that of that of fake news. This imbalance makes it difficult for SVM to learn the characteristics of the minority class (fake news), thus affecting the resulting precision and F1-Score values. SVM tends to provide more optimal results if the data between these datasets is balanced. Selecting an algorithm that can handle unbalanced data, such as Random Forest, is a more effective solution for automatically detecting fake news.

The dataset used in this study was compiled from multiple reputable sources, ensuring a mix of valid and fake news articles representative of the Indonesian context. However, the label distribution—100 valid news items and only 20 fake news items—resulted in a clear class imbalance. This imbalance posed a challenge for certain algorithms, particularly Support Vector Machine (SVM), which typically performs better with balanced datasets. The presence of this imbalance highlights the importance of either data augmentation techniques or algorithm selection strategies capable of handling skewed class distributions to maintain optimal classification performance.

The data preprocessing stage, which involved removing stopwords, numbers, and punctuation, successfully refined the dataset, allowing the classification models to focus on words with higher information value. The resulting word clouds and frequency analysis revealed that political terms dominated both valid and fake news categories. Words such as “Prabowo,” “Partai,” and “Ketua” were more prevalent in valid news, while “Jokowi,” “Presiden,” and “Pemilu” appeared frequently in fake news. This finding indicates that political narratives—particularly those related to key political figures and election events—are central to the dissemination of both factual and misleading information. Such patterns suggest that fake news detection models need to be particularly sensitive to political discourse, which may involve subtle linguistic differences between fact and misinformation.

In the model training phase, four algorithms—SVM, Random Forest, Long Short-Term Memory (LSTM), and Self-Organizing Map (SOM)—were tested to evaluate classification performance. The results showed that Random Forest achieved perfect precision, recall, and F1-score, outperforming the other models. This can be attributed to its ensemble-based decision-making process, which mitigates overfitting and maintains robustness even with unbalanced datasets. LSTM, while slightly lower in recall, demonstrated strong performance due to its capability in processing sequential text data, making it a valuable approach for natural language tasks. SOM also performed well, particularly in mapping high-dimensional text data into structured clusters.

Conversely, SVM recorded the lowest precision and F1-score, reflecting its sensitivity to class imbalance and limited ability to capture minority class characteristics without additional balancing strategies. This finding aligns with prior studies indicating that SVM may require preprocessing methods such as Synthetic Minority Over-sampling Technique (SMOTE) or cost-sensitive learning to improve performance in imbalanced datasets.

Overall, the results demonstrate that algorithm choice significantly affects fake news detection outcomes, with Random Forest emerging as the most effective in this context. Nonetheless, the political nature of both valid and fake news content suggests that future models should incorporate domain-specific linguistic features and possibly sentiment or stance detection to further enhance accuracy. Addressing dataset imbalance through resampling or adaptive weighting could also improve the detection of minority class instances, thereby strengthening the system’s reliability in real-world scenarios.

The dataset for this study was compiled from several credible sources, including Kaggle, Detik, Cek Fakta, and Turn Back Hoax, ensuring a diverse representation of both valid and fake news within the Indonesian context. However, the resulting label distribution—100 valid news items compared to only 20 fake news items—indicates a significant class imbalance. This imbalance presents a challenge for classification algorithms, as it can cause a model to bias toward the majority class and misclassify minority class instances (He & Garcia, 2009). Consequently, without appropriate handling, such as resampling or cost-sensitive learning, models may achieve high accuracy overall but perform poorly in detecting fake news, which is the more critical and rarer category in this context.

The preprocessing stage was designed to address the noise commonly found in raw text data, such as stopwords, punctuation, and numerical elements. The use of the Natural Language Toolkit (NLTK) stopwords library helped remove low-value terms that do not contribute meaningfully to classification (Priadana & Murdiyanto, 2020). This cleaning process improved the dataset's relevance and allowed the models to focus on features with higher discriminative power. Visual analysis through word clouds revealed that political terms dominated both categories. In valid news, words such as "Prabowo," "Partai," and "Ketua" were frequent, while in fake news, terms like "Jokowi," "Presiden," and "Pemilu" were more common. This confirms that political narratives, particularly those concerning prominent figures and electoral events, are a central theme in both factual and misleading news in Indonesia, echoing previous studies that highlight politics as a dominant domain for online disinformation (Allcott & Gentzkow, 2017; Tandoc et al., 2018; Melinda et al., 2024; Julianti et al., 2025).

In the model training phase, four algorithms—Support Vector Machine (SVM), Random Forest, Long Short-Term Memory (LSTM), and Self-Organizing Map (SOM)—were applied. Random Forest achieved the highest overall performance, obtaining perfect precision, recall, and F1-score on both training and testing datasets. This superior performance can be attributed to the ensemble nature of Random Forest, which combines multiple decision trees to reduce overfitting and improve generalization, especially in handling high-dimensional and partially imbalanced data (Breiman, 2001; Perdana et al., 2023; Zubair et al., 2025). LSTM also performed well, with strong recall and precision values, benefiting from its ability to process sequential text and capture contextual dependencies in news content (Hochreiter & Schmidhuber, 1997). SOM demonstrated competitive results, confirming its effectiveness in mapping high-dimensional data into low-dimensional representations for pattern recognition tasks (Kohonen, 2013).

Conversely, SVM recorded the lowest precision and F1-score among the tested models, primarily due to the dataset's imbalance. Previous research has shown that SVM's classification boundaries can be heavily influenced by dominant classes, resulting in reduced performance for minority class detection (Huang et al., 2016). Without balancing strategies such as the Synthetic Minority Over-sampling Technique (SMOTE) or class weighting, SVM tends to underperform in such contexts. This aligns with findings from Joachims (1998) that SVM models require careful feature scaling and balanced data distributions to achieve optimal results in text classification.

These findings underline two main insights. First, algorithm selection is crucial for fake news detection in imbalanced datasets, with ensemble-based methods like Random Forest providing more stable and accurate outcomes. Second, the political bias in both valid and fake news underscores the need for domain-specific feature engineering, including sentiment analysis, stance detection, and entity recognition, to improve classification accuracy. Future research should also prioritize addressing class imbalance through advanced resampling methods or adaptive cost functions, as suggested by Chawla et al. (2002), to enhance the reliability of fake news detection systems in real-world applications.

This study offers a novel contribution by conducting a direct comparative evaluation of four widely used classification algorithms—Support Vector Machine (SVM), Random Forest (RF), Long Short-Term Memory (LSTM), and Self-Organizing Map (SOM)—on a single standardized Indonesian news dataset with consistent preprocessing and evaluation criteria. Unlike prior research that often evaluates algorithms in isolation or on disparate datasets (Reis et al., 2019; Pahlevi et al., 2023), this study systematically assesses their performance under identical conditions, enabling a fair and reliable comparison. The incorporation of both traditional machine learning and deep learning models in one experimental framework provides a more comprehensive understanding of their strengths and weaknesses in detecting fake news. Furthermore, the study integrates domain-specific contextual analysis through word frequency and thematic mapping, revealing the dominance of political discourse in both valid and fake news—a factor often overlooked in purely technical evaluations. The results demonstrate that algorithm selection plays a critical role in achieving optimal fake news detection performance in imbalanced datasets. Random Forest's perfect precision, recall, and F1-score indicate that ensemble-based models are particularly effective for handling skewed class distributions, making them highly applicable for real-world scenarios where fake news is relatively rare (Breiman, 2001). The dominance of political terms in both valid and fake news suggests that detection models should incorporate domain-specific linguistic features, sentiment polarity, and stance analysis to distinguish subtle narrative differences. In practice, these findings can guide government agencies, fact-checking organizations, and social media platforms in choosing and adapting detection algorithms for large-scale deployment in the Indonesian context and potentially other politically sensitive environments.

The primary limitation of this study lies in the dataset size and imbalance—100 valid news items versus 20 fake news items. Although Random Forest managed the imbalance well, other algorithms, particularly SVM, were adversely affected. Additionally, the dataset is domain-specific to Indonesian political news, which may limit the model's generalizability to other topics or languages. The study also focuses solely on textual features, excluding multimodal data such as images, videos, or metadata, which could enhance detection accuracy in a broader fake news landscape (Shu et al., 2019). Future research should address data imbalance through techniques such as Synthetic Minority Over-sampling Technique (SMOTE), adaptive weighting, or data augmentation to improve minority class detection (Chawla et al., 2002). Expanding the dataset to include non-political and multilingual content would enhance generalizability. Additionally, integrating multimodal analysis and transformer-based architectures (e.g., BERT, RoBERTa) could capture richer contextual representations and improve classification accuracy. Collaboration with fact-checking organizations for real-time data collection could also make detection models more adaptive to emerging misinformation patterns.

CONCLUSION

This study concludes that among the four evaluated algorithms, Random Forest is the most effective for fake news detection in the Indonesian political news context, outperforming SVM, LSTM, and SOM in terms of precision, recall, and F1-score. The ensemble-based approach of Random Forest offers robustness against class imbalance and yields stable, high-accuracy results. However, the persistent influence of political discourse in both valid and fake news content highlights the need for domain-specific feature engineering to detect subtle differences between fact and misinformation. While the findings provide clear guidance on algorithm selection, addressing dataset limitations and incorporating advanced feature representations will be essential for building scalable, adaptable, and context-aware fake news detection systems suitable for broader real-world application.

ACKNOWLEDGMENTS

In many cases authors would like to express their gratitude or thanks to other bodies who generally support their work. Words are expressed in this section. Likewise, in many papers this section is skipped or omitted.

AUTHOR CONTRIBUTIONS

For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, X.X. and Y.Y.; Methodology, X.X.; Software, X.X.; Validation, X.X., Y.Y. and Z.Z.; Formal Analysis, X.X.; Investigation, X.X.; Resources, X.X.; Data Curation, X.X.; Writing – Original Draft Preparation, X.X.; Writing – Review & Editing, X.X.; Visualization, X.X.; Supervision, X.X.; Project Administration, X.X.; Funding Acquisition, Y.Y.".

CONFLICTS OF INTEREST

The author(s) declare no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the generation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

REFERENCES

Ahmad, F., & Ramasamy, L. (2019). A comparison of machine learning algorithms in fake news detection. *International Journal on Emerging Technologies, 10*(4), 1–7. Retrieved from https://www.researchgate.net/publication/337800975

Ajik, E. D., Obunadike, G. N., & Echobu, F. O. (2023). Fake news detection using optimized CNN and LSTM techniques. *Journal of Information Systems and Informatics, 5*(3), 1044–1057. https://doi.org/10.51519/journalisi.v5i3.548

Agustina, N., Adrian, A., & Hermawati, M. (2022). Implementasi algoritma naïve bayes classifier untuk mendeteksi berita palsu pada sosial media [Implementation of the naive Bayes classifier algorithm to detect fake news on social media]. *Faktor Exacta, 14*(4), 206. https://doi.org/10.30998/faktorexacta.v14i4.11259

Amanda, R., & Negara, E. S. (2020). Analysis and implementation machine learning for youtube data classification by comparing the performance of classification algorithms. *Jurnal Online Informatika, 5*(1), 61–72. https://doi.org/10.15575/join.v5i1.505

Andryani, R., Surya Negara, E., Syaputra, R., & Erlansyah, D. (2023). Analysis of academic social networks in Indonesia. *Qubahan Academic Journal*, *3*(4), 409–421. https://doi.org/10.48161/qaj.v3n4a289.

Fadhlullah, N., & Surahman, A. (2022). Penerapan Teknologi Web Scraping Sebagai Pengumpulan Data COVID-19 di Provinsi Lampung [Implementation of Web Scraping Technology for COVID-19 Data Collection in Lampung Province]. *Jurnal Informatika dan Rekayasa Perangkat Lunak (JATIKA), 3*(1), 25–30. Retrieved from https://radarlampung.co.id/?s=covid

Ghazi Arkaan, S., Atmadja, A. R., & Firdaus, M. D. (2024). Fake news detection in the 2024 indonesian general election using bidirectional long short-term memory (BI-LSTM) Algorithm. *Komputasi, 21*(2), 693–7554. https://doi.org/10.33751/komputasi.v21i2.5260

Homepage, J., & Aziz, S. (2022). Implementasi algoritma self organizing map untuk identifikasi pola pengelompokan tingkat kesejahteraan keluarga Kabupaten Siak. *IJIRSE: Indonesian Journal of Informatic Research and Software Engineering, 2*(2). https://doi.org/10.57152/ijirse.v2i2.431.

Hu, L., Yang, T., Zhang, L., Zhong, W., Tang, D., Shi, C., ... & Zhou, M. (2021, August). Compare to the knowledge: Graph neural fake news detection with external knowledge. In *Proceedings of the 59th annual meeting of the association for computational linguistics and the 11th international joint conference on natural language processing (volume 1: long papers)* (pp. 754-763).

Islam, T., Hosen, M. A., Mony, A., Hasan, M. T., Jahan, I., & Kundu, A. (2022, January). A proposed Bi-LSTM method to fake news detection. In *2022 International Conference for Advancement in Technology (ICONAT)* (pp. 1-5). IEEE.

Julianti, R. T., Sahiner, M., & Khalid, N. (2025). Utilization of MOOC for Subak Values Extension: Maintaining Balinese Local Wisdom in Modern Education. *Journal of Educational Technology and Learning Creativity*, *3*(1), 131-137. https://doi.org/10.37251/jetlc.v3i1.1569.

Marta, D., Ginting, G. L., & Sihite, A. H. (2022). Deteksi berita palsu tentang vaksinasi covid-19 dengan menggunakan text mining dan algoritma cosine similarity [Detecting fake news about Covid-19 vaccination using text mining and cosine similarity algorithms]. *Nasional Teknologi Informasi dan Komputer, 6*(1). https://doi.org/10.30865/komik.v6i1.5738

Melinda, S., Feizi , F., & Monfared , P. N. (2024). Transforming religious learning with macromedia flash 8: improving students' understanding of the material on faith in the apostles. *Journal of Educational Technology and Learning Creativity*, *2*(2), 201-208. https://doi.org/10.37251/jetlc.v2i2.1100.

Muzakir, A., & Suriani, U. (2023). Model deteksi berita palsu menggunakan pendekatan bidirectional long short-term memory (BiLSTM) [The fake news detection model uses a bidirectional long short-term memory (BiLSTM) approach]. *Journal of Computer and Information Systems Ampera, 4*(2). https://doi.org/10.51519/journalcisa.v4i2.397

Nadira, T. S., & Negara, E. S. (2020). Membangun basis data geolocation dari media sosial twitter untuk web berita online [Building a geolocation database from social media twitter for online news websites]. In *Bina Darma Conference on Computer Science (BDCCS)*, 2(5), 317-325.

Nayoga, B. P., Adipradana, R., Suryadi, R., & Suhartono, D. (2021). Hoax analyzer for Indonesian news using deep learning models. *Procedia Computer Science, Elsevier B.V.*, 704–712. https://doi.org/10.1016/j.procs.2021.01.059

Negara, E. S., & Andryani, R. (2018). A review on overlapping and non-overlapping community detection algorithms for social network analytics. *Far East Journal of Electronics and Communications, 18*(1), 1–27. https://doi.org/10.17654/ec018010001.

Negara, E. S., Keni, K., Andryani, R., Syaputra, R. S., & Widyanti, Y. (2023). Social network analysis to detect influential actors with indonesian hashtags using the centrality method. *AIP Conference Proceedings, 2680*(1), 020167. https://doi.org/10.1063/5.0126819

Nurhachita, & Negara, E. S. (2021). A comparison between deep learning, naïve bayes and random forest for the application of data mining on the admission of new students. *IAES International Journal of Artificial Intelligence, 10*(2), 324–331. https://doi.org/10.11591/ijai.v10.i2.pp324-331

Pahlevi, R., Negara, E. S., Sutabri, T., & Herdiansyah, M. I. (2023). Penerapan metode naive bayes untuk menentukan klasifikasi kelayakan penerimaan bantuan rehabilitasi dan pembangunan sekolah [Application of the naive Bayes method to determine the classification of eligibility for receiving school rehabilitation and construction assistance]. *JTIK, 9*(2), 1176–1188. https://doi.org/10.37012/jtik.v9i2.1790

Perdana, F. A., Zakariah, S. H., & Alasmari, T. (2023). Development of learning media in the form of electronic books with dynamic electricity teaching materials. *Journal of Educational Technology and Learning Creativity*, *1*(1), 1-6. https://doi.org/10.37251/jetlc.v1i1.619.

Pérez-García, F., Sparks, R., & Ourselin, S. (2021). TorchIO: a Python library for efficient loading, preprocessing, augmentation and patch-based sampling of medical images in deep learning. *Computer methods and programs in biomedicine*, *208*, 106236. https://doi.org/10.1016/j.cmpb.2021.106236

Priadana, A., & Murdiyanto, A. W. (2020). Instagram hashtag trend monitoring using web scraping. *Journal Pekommas, 5*(1), 23. https://doi.org/10.30818/jpkm.2020.2050103

Ramadhan, N. G., Adhinata, F. D., Segara, A. J. T., & Rakhmadani, D. P. (2022). Deteksi berita palsu menggunakan metode random forest dan logistic regression. *JURIKOM (Jurnal Riset Komputer), 9*(2), 251. https://doi.org/10.30865/jurikom.v9i2.3979

Reis, J. C. S., Correia, A., Murai, F., Veloso, A., Benevenuto, F., & Cambria, E. (2019). Supervised learning for fake news detection. *IEEE Intelligent Systems, 34*(2), 76–81. https://doi.org/10.1109/MIS.2019.2899143

Religia, Y., Nugroho, A., & Hadikristanto, W. (2021). Klasifikasi analisis perbandingan algoritma optimasi pada random forest untuk klasifikasi data bank marketing [Classification comparative analysis of optimization algorithms on random forest for bank marketing data classification]. *Jurnal RESTI, 5*(1), 187–192. https://doi.org/10.29207/resti.v5i1.2813

Shu, K., Mahudeswaran, D., & Liu, H. (2019). FakeNewsTracker: A tool for fake news collection, detection, and visualization. *Comput Math Organ Theory, 25*(1), 60–71. https://doi.org/10.1007/s10588-018-09280-3

Shu, K., Sliva, A., Wang, S., Tang, J., & Liu, H. (2017). Fake news detection on social media: A data mining perspective. *ACM SIGKDD explorations newsletter*, *19*(1), 22-36. https://doi.org/10.1145/3137597.3137600.

Singhal, S., Shah, R. R., Chakraborty, T., Kumaraguru, P., & Satoh, S. (2019). SpotFake: A Multi-modal Framework for Fake News Detection. In 2019 *IEEE Fifth International Conference on Multimedia Big Data (BigMM)* (pp. 39–47). https://doi.org/10.1109/BigMM.2019.00-44

Sugiarta, A. I., Syamsuar, D., & Negara, E. S. (2018). Analisis sentralitas aktor pada struktur jaringan politik dengan menggunakan metode social network analysis (sna): Studi kasus group facebook lembaga survei sosial media. *Seminar Nasional Teknologi Informasi dan Komunikasi (SEMNASTIK) X*.

Yunanto, R., Purfini, A. P., & Prabuwisesa, A. (2021). Survei literatur: Deteksi berita palsu menggunakan pendekatan deep learning [Literature survey: Fake news detection using deep learning approach]. *Jurnal Manajemen Informatika (JAMIKA)*, *11*(2), 118-130. https://doi.org/10.34010/jamika.v11i2.493.

Zubair, S., Alyousfi, E. A., & Khan, S. A. (2025). New media and children's social development: A case study of digital technology use among 8–12-Year-Olds in Pakistan. *Journal of Educational Technology and Learning Creativity*, *3*(1), 107-114. https://doi.org/10.37251/jetlc.v3i1.1730.