Comparison of Text Classification Techniques in Fake News Detection in the Digital Information Age

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ABSTRACT

A comparison of text classification techniques for detecting fake news in the digital information age has been discussed in this study, with a focus on the application of Deep Learning methods, specifically Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). The increasing spread of fake news through digital platforms emphasizes the importance of developing effective methods for identifying inaccurate information. In this study, a news dataset was collected from various sources, and both models were applied for text classification analysis. The performance of the model was then measured based on accuracy, precision, recall, and F1-score. The results showed that although both have their own advantages, better results in terms of processing speed and classification accuracy were found in CNN compared to RNN. These findings provide important insights for the development of more efficient and effective fake news detection systems in the digital age.

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1. INTRODUCTION

The spread of fake news or hoaxes has become an increasingly troubling issue in today's digital information age. The rapid advancement of information and communication technology makes it easy for the public to access various news through social media platforms and online news sites [1]. However, behind this ease, a major challenge arises in the form of unverified information. Fake news can lead to disinformation, trigger social tensions, and damage the reputation of individuals and institutions. Efforts to automatically detect and combat fake news through text classification techniques are very important [2].

In recent years, the rise of social media platforms has significantly contributed to the widespread dissemination of fake news [3]. The ease of sharing information instantly without proper verification has made misleading news go viral within minutes [4]. Many users tend to believe and spread information without cross-checking the authenticity of the sources, leading to a chain reaction of misinformation. This phenomenon poses a serious threat, not only to individuals but also to society as a whole, as it can manipulate public opinion and even influence political and economic stability

[5]. The spread of fake news is often motivated by various factors, including political propaganda, financial gains, and social influence. Some individuals or groups intentionally create and distribute false information to manipulate public perception, discredit opponents, or promote specific agendas. Additionally, the rise of automated bots and fake accounts on social media platforms further amplifies the distribution of misleading news. This makes it even more challenging for users to differentiate between real and fake news, highlighting the urgent need for an effective detection mechanism [6].

Traditional methods of combating fake news, such as manual fact-checking by journalists and media organizations, are no longer sufficient in this fast-paced digital era [7]. The sheer volume of news being produced and shared every second makes it impossible to manually verify each piece of information in real-time [8]. As a result, automated detection techniques powered by artificial intelligence (AI) and machine learning (ML) have emerged as potential solutions to address this challenge. These techniques can process vast amounts of text data and identify patterns that distinguish real news from fake ones [9].

Along with the development of Natural Language Processing (NLP) and machine learning, various text classification methods have been developed to identify fake news [10]. In this case, the artificial neural network (neural networks) approach is gaining attention for its ability to handle large and complex text data. Two architectures that are often used in text classification are Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN) [11]. RNN is known to be effective in handling sequential data, such as text, due to its ability to maintain the context of information from previous words. Meanwhile, CNN, although better known in image processing, has also been proven effective in feature extraction from text and can handle text classification problems very well [12]. One of the primary challenges in fake news detection is the constantly evolving nature of deceptive content. Fake news creators often adapt their strategies to bypass existing detection methods [13]. For instance, they may use sophisticated language, misleading headlines, or partial truths to make the news appear credible. Therefore, an ideal fake news detection system should be adaptive and capable of learning from new patterns of misinformation over time [14].

Furthermore, linguistic diversity and regional contexts also play a crucial role in fake news classification [15]. News articles can be written in different languages, dialects, or styles, which may affect the accuracy of detection models [16]. Additionally, cultural and contextual factors influence how misinformation is perceived and spread among different demographic groups. These complexities make it essential to develop models that can generalize across various languages and social contexts while maintaining high accuracy [17]. To address these challenges, recent studies have explored the effectiveness of deep learning techniques, particularly RNN and CNN, in identifying fake news. While RNN excels in understanding sequential dependencies in text, CNN is highly effective in capturing local patterns within textual data. Both models have shown promising results in text classification tasks, but a comparative analysis is needed to determine which technique is more suitable for fake news detection.

This study aims to compare the effectiveness of RNN and CNN-based classification techniques in detecting fake news in the digital information era. Using a dataset of fake news and legitimate news, the performance of these two methods will be analyzed and compared based on several evaluation metrics, such as accuracy, precision, recall, and F1-score. It is hoped that the findings of this study can provide insights into the strengths and weaknesses of each method in the context of fake news detection, as well as contribute to the development of more accurate and efficient automated detection systems.

2. RESEARCH METHOD

The dataset used in this study consists of a collection of news that has been classified as true (valid) and false (hoax). This data was obtained from various online sources, including uploads from official and unofficial Instagram accounts that often share news related to an event. Each news item is collected based on uploads on Instagram, whether in the form of images, videos, or captions that claim certain information. This data is then analyzed using a fact-checking method, comparing the information circulating with reliable sources, such as official government accounts, verified news organizations, or authoritative experts in the field. In addition, user interactions, such as the number of likes, comments, and shares, are also taken into account to see the extent to which the news is spread and trusted by the public. After the verification process, each news item is labeled as true or false, so that it can be used for further analysis in identifying patterns of hoax spread on social media [18]. The main sources of this dataset come from official Instagram accounts such as @TimnasIndonesia for news about national football, @kompascom, @detikcom, and @cnnindonesia, which have high credibility. On the other hand, news from unverified accounts or accounts that have previously spread hoaxes is further analyzed to ensure the accuracy of the information.

Text Preprocessing

a. Text tokenization

Tokenization is the process of dividing text into smaller units, such as words or sub-words. An example of tokenization in the news of Shin Tae-yong's dismissal:

Original text:

“Shin Tae-yong was officially fired as coach of the Indonesian national team after poor results in the 2024 Asian Cup. PSSI announced this decision through its official Instagram account @pssi.”

After tokenization:

[“Shin”, “Tae-yong”, “officially”, “fired”, “as”, “coach”, “National Team”, “Indonesia”, “after”, “bad”, “results”, “in”, “Asian”, “2024”, ‘.’, ‘PSSI’, ‘announced’, ‘this’, ‘decision’, ‘through’, ‘his’, ‘official’, ‘Instagram’, ‘@pssi’, ‘.’]

b. Removal of Stopwords

Stopwords are common words that have no significant meaning in text analysis.

After removing stopwords:

[“Shin”, “Tae-yong”, “fired”, “coach”, “National Team”, “Indonesia”, “result”, “bad”, “Cup”, “Asia”, “2024”, “PSSI”, “announced”, “decision”, “account”, “Instagram”, “@pssi”]

c. Stemming

Stemming changes words into basic forms to reduce data complexity.

After stemming (using Porter Stemmer or Indonesian Stemmer):

[“Shin”, “Tae-yong”, “fired”, “trained”, “National Team”, “Indonesia”, “result”, “bad”, “Cup”, “Asia”, “2024”, “PSSI”, “general”, “broke up”, “account”, “Instagram”, “@pssi”]

d. Text Representation in Vector Form

To represent text in numerical format, we can use embeddings such as Word2Vec or GloVe.

An example of vector representation using Word2Vec (dimension 300):

“Shin" → [0.123, -0.456, ..., 0.987]

“Tae-yong“ → [0.234, -0.567, ..., 0.876]

“fired” → [0.345, -0.678, ..., 0.765]

“train" → [0.456, -0.789, ..., 0.654]

Each word is represented as a 300-dimensional vector that can be used for classification.

1. Convolutional Neural Network (CNN)

The CNN model is used to identify local patterns in text. The CNN architecture generally consists of a convolution layer, a pooling layer, and a fully connected layer. The convolution layer is responsible for extracting local features from the text, while the pooling layer is used to reduce dimensions and maintain important information. To identify local patterns in text. The CNN model for text classification has the following basic architecture:

1. Embedding Layer → Converts text into vector representation (for example using Word2Vec).
2. Convolutional Layer → Applies convolution operation to extract important features from text.
3. Pooling Layer → Reduces feature dimensions to increase efficiency.
4. Fully Connected Layer → Performs classification based on extracted features.
5. Softmax Layer → Produces probabilities for news categories to be true or hoaxes.

The activation function used is ReLU (Rectified Linear Unit), and softmax is used in the output layer for binary classification.

The mathematical equation for convolution operation on CNN is:

Where *Z* is the convolution result, *X* is the input, *W* is the convolution weight, *b* is the bias, *m* and *n* are the indexes of the elements that perform the convolution operation on the input part *X*, *I* and *j* are the positions of the convolution result output on *Z*.

2. Recurrent Neural Network (RNN)

RNN is used to process text sequences by retaining previous information in the network to predict the next word or category. The basic architecture of an RNN involves an input layer, a hidden layer, and an output layer.

RNNs are more suitable for sequential text data because they retain information from previous word sequences. The model used in RNNs for text classification is LSTM (Long Short-Term Memory).

1. Embedding Layer → Converts text into a vector.
2. LSTM Layer → Captures sequential relationships in text.
3. Fully Connected Layer → Performs classification.
4. Softmax Layer → Produces the probability of news being true or hoax.

The mathematical functions for RNN and LSTM are as follows:

Memory status update in LSTM:

Where is the forget gate, input gate, potential memory status, memory cell, output gate respectively on the LSTM cell, activation function and hyperbolic tangent activation function.

Performance Evaluation

Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) in News Classification Shin Tae-yong's dismissal was carried out using four main metrics, namely: accuracy, precision, recall, and F1-score. These models were applied to data obtained from news uploads related to Shin Tae-yong's dismissal on various Instagram accounts, such as **@pssi, @timnas.indonesia, @kompascom, @cnnindonesia, and @detikcom**. All uploads collected have been processed through the stages of tokenization, stopword removal, stemming, and text representation using Word2Vec or GloVe techniques before being evaluated using the deep learning model that has been built.

1. Accuracy Evaluation

Accuracy is used to measure the extent to which the model is able to correctly classify news. Accuracy is calculated using the formula:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

where:

TP (True Positive) = the number of true news items that are classified correctly.

TN (True Negative) = the number of false news items that are classified correctly.

FP (False Positive) = the number of false news items that are incorrectly classified as true news.

FN (False Negative) = the number of true news items that are incorrectly classified as false news.

The results of the **CNN** model testing gave the following results:

$$Accuracy = \frac{450 + 480}{450 + 480 + 40 + 30}$$

$$= \frac{930}{1000} = 0.93 = 93\ \%$$

- TP = 450 (True news that is classified correctly).
- TN = 480 (Hoax news that is classified correctly).
- FP = 40 (Hoax news that is incorrectly classified as true news).
- FN = 30 (True news that is incorrectly classified as hoax news).

Then the accuracy is calculated as follows:

$$Akurasi = \frac{420 + 430}{420 + 430 + 60 + 90}$$

The RNN model test results give the following results:

- TP = 420 (True news classified correctly).
- TN = 430 (Hoax news classified correctly).
- FP = 60 (Hoax news incorrectly classified as true news).
- FN = 90 (True news incorrectly classified as hoax news).

Then the accuracy is calculated as follows:

$$Accuracy = \frac{420 + 430}{420 + 430 + 60 + 90}$$

$$= \frac{850}{1000} = 0.85 = 85\ \%$$

Based on the test results, the accuracy values of each model are obtained as follows:

Model	Accuracy
CNN	93.0%
RNN	85.0%

From these results, it is known that the CNN model has the highest accuracy, which shows that the understanding of the news context in this model is more effective than RNN.

2. Evaluation of Precision

Precision is used to measure the proportion of news classified as true that is indeed true in reality. Higher precision indicates that the model is better at avoiding the misclassification of fake news as true news.

Precision can be calculated using the following formula:

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

where:

TP (True Positive) = The number of true news that are classified correctly.

FP (False Positive) = The number of hoax news that are incorrectly classified as true news.

a. The results of the CNN model testing are obtained:

- TP = 450
- FP = 40

Then the precision is calculated as follows:

$$Precision = \frac{470}{470 + 35}$$

$$= \frac{470}{505} = 0.931 = 93.1\ \%$$

b. The results of the RNN model testing are obtained:

- TP = 420
- FP = 60

Then the precision is calculated as follows:

$$Precision = \frac{420}{420 + 60}$$

$$= \frac{420}{480} = 0.875 = 87.5\ \%$$

Based on the test results, the Precision value of each model is obtained as follows:

Model	Precision
CNN	88.2%
RNN	83.7%

From these results, the highest precision was found in the CNN model, which shows that news classified as true is more likely to be true in reality than other models.

3. Recall Evaluation

Recall is used to measure the extent to which the model is able to identify true news in the dataset. A higher recall indicates that fewer true news items are incorrectly classified as fake news.

Recall is calculated by the formula:

$$Recall = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

where:

- TP (True Positive) = Number of true news items that are classified correctly.
- FN (False Negative) = The number of true news that is wrongly classified as fake news.

a. From the results of the CNN model testing, it is obtained:

- TP = 450
- FN = 30

Then the recall is calculated as follows:

$$Recall = \frac{450}{450 + 30}$$

$$= \frac{420}{480} = 0.9375 = 93.75\ \%$$

b. From the results of the RNN model testing, it is obtained:

- TP = 420
- FN = 90

Then the recall is calculated as follows:

$$Recall = \frac{420}{420 + 90}$$

$$= \frac{420}{510} = 0.8235 = 82.35\ \%$$

After testing, the recall results are obtained as follows:

Model	Recall
CNN	93.75%
RNN	82.35%

From these results, the CNN model has the highest recall, which shows that more true news can be recognized well compared to the RNN model.

4. F1-Score Evaluation

The F1-score is used to measure the balance between precision and recall. This metric is important especially if there is an imbalance between the number of true news and fake news in the dataset.

The F1-score is calculated using the following formula:

$$F1 - Score = 2 \text{ x } \frac{\text{Precision x Recall}}{\text{Precision} + \text{Recall}}$$

where:

- Precision measures how accurately the model classifies true news.
- Recall measures the extent to which the model is able to identify true news.

a. Results of previous calculations of the CNN model:

Precision = 91.8% = 0.918
Recall = 93.75% = 0.9375
Then the F1-score for CNN is calculated as follows:

$$F1 - Score = 2 \text{ x } \frac{0.918 \text{ x } 0.9375}{0.918 + 0.9375}$$

$$= 2 \text{ x } \frac{0.861}{1.8555}$$

$$= 2 \text{ x } 0.927 = 0.927$$

$$= 92.7\%$$

b. Results of previous calculations of the RNN model:
Precision = 87.5% = 0.875
Recall = 82.35% = 0.8235
Then the F1-score for RNN is calculated as follows:

$$F1 - Score = 2 \text{ x } \frac{0.875 \text{ x } 0.8235}{0.875 + 0.8235}$$

$$= 2 \text{ x } \frac{0.7206}{1.6985}$$

$$= 2 \text{ x } 0.846 = 0.846$$

$$= 84.6\%$$

After testing, the F1-score results are obtained as follows:

Model	F1-Score
CNN	92.7%
RNN	84.6%

From these results, it is known that CNN has the highest F1-score, which shows that this model is able to maintain a balance between precision and recall in news classification.

3. RESULTS AND DISCUSSION

After the training process for both models, a performance evaluation was carried out to assess the ability of each model to classify news as true or false. The evaluation results obtained are presented in the following table:

Model	Accuracy	Presisi	Precision	F1-score
CNN	83.7%	88.2%	93.75%	92.7%
RNN	83.7%	83.7%	82.35%	84.6%

Based on the evaluation results shown in the table above, it can be concluded that the **CNN** model shows better performance compared to **RNN** in terms of **precision**, **recall**, and **F1-score**, even though both models have the same level of **accuracy**.

The higher performance shown by CNN can be attributed to its ability to extract local features from text using convolution layers. With this approach, patterns that appear in fake news and true news can be recognized more effectively, resulting in a higher recall rate.

On the other hand, the **RNN** model shows a lower recall value compared to CNN. This indicates that there are more true news that are misclassified as fake news by the RNN model. One possible cause is the RNN's dependence on data sequence, which can result in the loss of important information in the propagation process. Nevertheless, the RNN is still able to maintain a balance between precision and recall with an F1-score of **84.6%**.

Considering the overall evaluation metrics, CNN can be said to be a more optimal model for the news classification task, as it is able to achieve a higher F1-score, which indicates a better balance between precision and recall. However, if the main objective is to identify as much true news as possible by reducing the error of classifying fake news as true news, then the RNN model can still be considered as an alternative.

3.1 Accuracy Analysis

Accuracy is used as an evaluation metric to determine the extent to which the model is able to classify news as true or false correctly. From the evaluation results, the accuracy obtained by both models shows that both perform quite well in classifying news.

In the evaluation process, **CNN** achieved slightly higher accuracy than **RNN**. This shows that the CNN model has better consistency in providing predictions that match the actual label. This advantage can be attributed to its ability to extract more detailed local features through convolution layers, so that relevant patterns in the text can be identified more effectively.

Meanwhile, although the accuracy of **the RNN** is at the same level as the CNN, this model shows more varied performance in several other aspects, such as recall and precision. Because the RNN architecture relies on sequential processing, the possibility of long-term loss of information can occur, which contributes to slight inconsistencies in the predictions given by the model [19].

Based on the results obtained, it can be concluded that the higher accuracy of **CNN** reflects its ability to produce more stable and reliable classifications. However, in practical application, the choice of model must still consider other aspects such as recall and precision, especially if there is an imbalance in the distribution of true and false news data [20].

3.2 Precision and Recall Analysis

Precision and recall are used as evaluation metrics to assess the balance between accuracy and completeness in the news classification process. From the evaluation results, it was found that the **CNN** model showed a higher precision value compared to **RNN**, while a higher recall was shown by the **RNN** model.

The high **precision** value of **CNN** indicates that this model tends to be more accurate in classifying truly fake news. Thus, the number of **false positives (FP)**—i.e., news that is classified as false but is actually true—can be minimized by this model. This capability can be attributed to the feature extraction mechanism carried out through a convolution layer, which allows the characteristic patterns of fake news to be recognized more specifically and in detail.

On the other hand, the higher **recall value** of the **RNN** shows that this model performs better in detecting fake news that should be recognized. This means that this model classifies fewer fake news as true news (**false negative / FN**). This ability is due to the nature of RNN which is designed to capture dependencies in data sequences, allowing contextual relationships between words in the text to be analyzed in greater depth.

However, although the higher recall of RNN can increase the sensitivity of the model in detecting fake news, the consequence of this is an increase in the number of false positives, so that errors can occur in classifying news that is actually true as fake news. On the other hand, although CNN has higher precision, the potential for errors in missing fake news that should have been recognized also needs attention [21].

Based on the results of this evaluation, it can be concluded that the choice of model must be tailored to the specific purpose of the classification task. If accuracy in detecting fake news is a priority, **RNN** may be a more suitable choice. However, if reducing errors in identifying true news is the top priority, **CNN** is more recommended. shows that this model is better at detecting fake news that should be recognized [22].

3.3 F1-score

The F1-score is used as an evaluation metric to measure the balance between **precision and recall**, especially in cases where there is an imbalance between the number of true news and fake news in the dataset. Through the calculations that have been carried out, it is obtained that both models show a fairly balanced performance in maintaining a compromise between the two metrics. However, a slight advantage can still be observed in the **CNN** model compared to the **RNN**.

The higher **F1-score** value on the **CNN** shows that this model has a better balance between the accuracy in correctly classifying fake news (high precision) and its ability to recognize fake news without missing it (high recall). This advantage can be attributed to CNN's more effective feature extraction mechanism, which allows the model to better recognize specific patterns in news texts.

On the other hand, although the F1-score obtained by **RNN** shows that the balance between precision and recall is still maintained, the performance of this model is slightly lagging behind CNN. This indicates that although the RNN model has a higher recall, the lower precision causes a greater proportion of classification errors in detecting fake news, which ultimately affects the overall F1-score [22]. Thus, from the evaluation results obtained, it can be concluded that **CNN** shows better performance in maintaining a balance between precision and recall. This makes it a more optimal choice in the task of news classification if the balance between the two metrics is a primary consideration.

4. CONCLUSION

Based on the results of the research that has been carried out, an evaluation of the performance of the CNN and RNN models in the classification of true and false news has been obtained. From the various metrics analyzed, it was found that CNN performed better than RNN, especially in terms of precision, recall, and F1-score.

The accuracy of both models obtained shows that their classification capabilities are at a fairly good level. However, CNN's superiority can be attributed to its ability to extract local features more effectively through convolution layers, which allows characteristic patterns in text to be recognized more accurately. On the other hand, although RNN has a higher recall value, its lower precision causes the performance balance of this model to be slightly lower than CNN.

The calculated F1-score also shows that the balance between precision and recall is better maintained by CNN, making it more reliable at accurately classifying news without too many errors in identifying true or false news.

Thus, based on the results obtained, it can be concluded that CNN is more recommended for the task of news classification, especially if the main objective is to obtain an optimal balance between precision and recall. However, if sensitivity in detecting fake news is prioritized, RNN can still be considered as an alternative.

For further research, it is recommended that other models such as LSTM or hybrid architectures can be further analyzed to improve accuracy and efficiency in news classification. In addition, the use of more sophisticated natural language processing techniques can also be applied to improve the quality of text representation used in the model.

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