Published online on the journal's webpage: **http://journal.ittelkom-pwt.ac.id/index.php/dinda**

Journal of Dinda

Data Science, Information Technology, and Data Analytics

Vol. 4 No. 1 (2024) 28 - 34 E-ISSN: 2809-8064

Identifying Fake News Using Long-Short Term Memory Model

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Abstract

Designed to deceive readers and manipulate public opinion, fake news can be created for a variety of reasons ranging from political propaganda to generating revenue through clickbait. Another significant challenge in combating fake news is the difficult balance between curbing misinformation and preserving free speech, though some argue for stricter regulations to control the spread of fake news. Thus, the purpose of this study is to identify fake news using Long-Short Term Memory (LSTM). LSTM models are often used to analyze the linguistic features of news articles or social media posts. The dataset we used comes from a dataset of fake news on Kaggle's website. The proposed method can identify fake news with average precision, recall, accuracy, and f-measure values of 0.94, 0.96, 0.94, and 0.95. The results showed that LSTM provides superior performance compared to the Support Vector Classifier, Logistic Regression, and Multinomial Naive Bayes methods.

Keywords: Fake News Classification, LSTM, Deep Learning

1. Introduction

Designed to deceive readers and manipulate public opinion, fake news can be created for a variety of reasons ranging from political propaganda to generating revenue through clickbait [1], [2]. The consequence of fake news is the erosion of trust in reliable sources of information, while sowing confusion and polarization in society.

The rise of social media platforms and the ease of sharing information online have played an important role in the spread of fake news, these platforms often prioritizing engagement and virality over accuracy [3]. Fake news can easily overshadow well-researched real news, further complicating the task of separating fact and fiction [4].

Another significant challenge in combating fake news is the difficult balance between curbing misinformation and preserving free speech, although some argue for stricter regulations to control the spread of fake news [5]. Implementing such measures without violating individual rights can be complicated. The challenge lies in a balance that limits the spread of false information while upholding the principles of freedom of expression and a dynamic and diverse marketplace of ideas [6].

Classification of fake news using the Long-Short Term Memory (LSTM) classification model is an innovative approach that aims to effectively combat the spread of misinformation [7]. By leveraging the capabilities of LSTM networks, the model can analyze linguistic patterns and contextual cues in news articles or social media posts to accurately classify them as trustworthy or fake news [8]. LSTM's strength lies in its ability to capture long-term dependencies in textual data, thus allowing it to identify complex patterns and subtle indicators of falsehood [9].

In this study LSTM is often used to analyze the linguistic features of news articles or social media posts [10]. This network can extract information about the tone, sentiment, and writing style used in the text, which can be indicative of potential misinformation [11]. By incorporating LSTM models into existing fake news detection frameworks, the researchers aim to improve the accuracy and effectiveness of the detection process [12]. The LSTM network offers powerful tools for capturing sequential and contextual information in news texts, thus enabling researchers to develop more robust models and algorithms to combat the spread of fake news [13].

The spread of fake news is an alarming phenomenon with profound social implications. Addressing this issue requires a multi-faceted approach involving active participation from media outlets, online platforms, individuals, and policymakers [14]. Educating the public about media literacy, promoting responsible journalism, and investing in robust fact-checking efforts are critical components in combating the spread of misinformation

Received: 29-02-2024 | Revised: 04-03-2024 | Published: 04-03-2024

[15]. By working together towards a more informed and critical society, we can reduce the harm caused by fake news and maintain the integrity of public discourse [16].

Hilman Bayu Aji, *et al*. [17] conducted a study entitled Detecting Hoax Content on Social Media Using Bi-LSTM and RNN. This research focuses on the DNN (Deep Neural Network) method which uses various models such as LSTM, Bi-LSTM, Bi-GRU and 1D-CNN around 96.90%. and also using the TF-IDF and Glove 88.59% methods and through a hybrid approach consisting of two variants, namely LSTM and LSTM-RNN 82%. and the effective learning-based method that is CNN.

Fajar Maulana, *et al*. [18] conducted a research entitled Hoax Classification in Indonesian Language with Bidirectional Temporal Convolutional Network Architecture. This research focuses on the Bi-TCN (Bi-Directional Temporal Convolutional Network) method used as the main architecture and TCN is a variation of CNN which is dilated-causal. This research emphasizes the development of user-friendly models by integrating them into websites.

Jasman Pardede *et al.* [19] conducted a research entitled Implementation of Long Short-Term Memory for Identification of English Hoax News on Social Media. This research focuses on LSTM (Long Short-Term Memory) method with data processing involving steps such as case folding, punctuauion removal, stopword removal and tokenization. Use model testing with separate data testing. In the evaluation stage, it uses metrics such as precision, recall, accuracy and f-measure with the help of confusion matrix to measure the performance of the LSTM model.

Junita Amalia, *et al*. [20] Conducted classification research using news data that has labels of fact news and fake news. The news classification process uses LSTM's Bidirectional technique and uses the CBOW architecture in Word2vec as word vectorization in building a news classification model. There are three main parameters used in the final project research, namely embedding size, windows size, and bilstm units. Optimization of model performance will be seen from the influence of these three parameters. The performance of the built model is measured using evaluation metrics accuracy, recall, precision, f1- score and computational time.

Rani Kurnia Putri, *et al*. [21] Conducted a research where a system was built that was able to identify hoax news or open hoaxes related to the coronavirus issue using the Long Short-Term Memory (LSTM) algorithm. LSTM networks are a type of recurrent neural networks that belong to the complex area of deep learning, these algorithms that try to mimic the way the human brain operates and uncover fundamental relationships in a given sequential data. The results of the study showed that the average value obtained was 51.09% for the precision value, 51.00% for the Recall value equal to the calculation of the Accuracy results and 50.41% for the F-Measure value.

2. Research Methods

This study proposes a research diagram as shown in Figure 1 below. Utilizing a robust dataset of Fake News scams sourced from Kaggle, we proceed to use a variety of methods. We analyze and process those datasets, so we can see patterns and correlations with great accuracy and precision. to identify and categorize examples of Fake News.

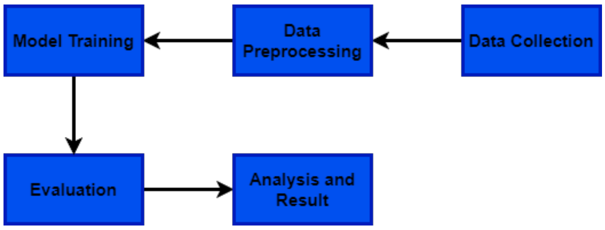

Figure 1. Diagram penelitian yang diusulkan

2.1. Data Collection

We obtained a dataset of fake news from Kaggle. The data set used for analysis and exploration in this research project consisted of a total of 72,134 news articles, with a clear dichotomy between real and fake news. From a vast pool of news articles, 35,028 articles were categorized as original news. On the other hand, the dataset also includes many 37,106 articles classified as fake news, which were deliberately created and disseminated to deceive the audience and spread misinformation. The clear separation between genuine and fake news in this dataset provides a unique opportunity for researchers to analyze significant patterns and characteristics to develop accurate and robust approaches to identifying fake news.

2.2. Data Processing

In the data processing step, an important stage in the research pipeline, textual data is converted into numerical vector representations, allowing classification models to effectively distinguish between fake news and genuine news [20]. To achieve this, several important processing techniques are applied. First, punctuation marks such as periods, commas, and exclamation marks are omitted from the text, as they do not contribute to the semantic meaning of the content. In addition, nonessential words, such as common clothing such as "the", "a", and "an", were eliminated from the data, as they generally had minimal contextual significance [22].

Next, the text data is broken down into words, to facilitate further analysis and feature engineering. Finally, the frequency with which each word occurs is calculated, yielding valuable insights into the prominence and relevance of a particular term in the data set. Thus, increasing the accuracy of classification of fake news and real news.

2.3. Model Training

The goal of this stage is to build an LSTM model that can distinguish between fake news and real news. LSTM models can be adapted to different architectures and hyperparameters [23], [24]. Data cleaning and processing is done before training the model to convert text data into numeric format. With proper preprocessing, LSTM models can learn patterns and make accurate predictions.

2.4. Evaluation

At this stage, we check how well the LSTM model performs using several important measures. Accuracy tells us how often the model correctly predicts for fake news and real news. Precision tells us how often a model correctly says a fake news article out of all articles labeled as fake. On the other hand, recall measures how often the model correctly predicts that a genuine news article is genuine from all existing original news articles. Using these measures, we can find out how well we are at correctly identifying fake news and genuine news.

2.5. Analysis and Result

This stage aims to analyze the results of the trial and understand the most important factors to identify fake news. The results of the analysis can be visualized to make them easier to understand. Make it easier to understand.

3. Results and Discussion

This study aims to determine the highest probability value based on fake and genuine (non-hoax) categories by applying LSTM techniques [25]. The training data is divided into 80 training data, 10 validation data, and 10 test data. This model was made with 150 epochs, 32 batch sizes, and 50 layers of LSTM [20].

In this study, experiments were conducted with dropout values ranging from 0.20, 0.25, 0.3, 0.35, 0.4, 045, and 0.5 with the same epoch and batch size. In Figure 2 through Figure 14, the (x) axis represents epoch information from 0 to 150, the (y) axis represents the value information of each loss and accuracy, the blue line represents the training data, and the orange color represents the graph flow data The lines shown are the graphical flow of validation data. Figures 2, 4, 6, 8, 10, 12, 14 represent the loss plots for dropout values 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, and Figures 3, 5, 7, 9, 11, 13 are and 15 are the precision values respectively failed.

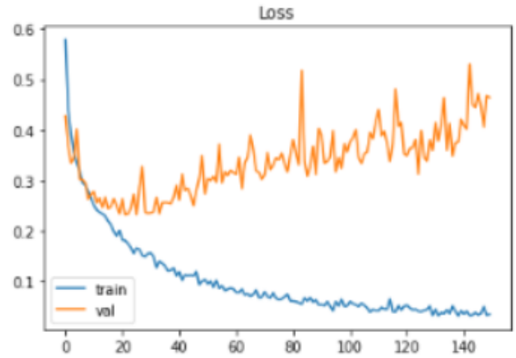

Figure 2. Loss Results with a Dropout Value of 0.2

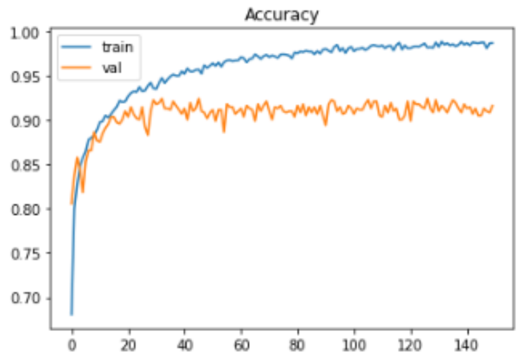

Figure 3. Accuracy Results with a Dropout Value of 0.2

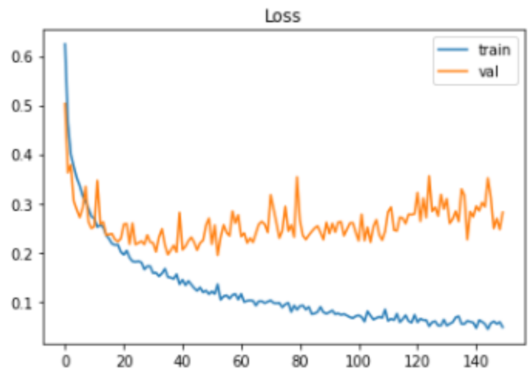

Figure 4. Loss Results with a Dropout Value of 0.25

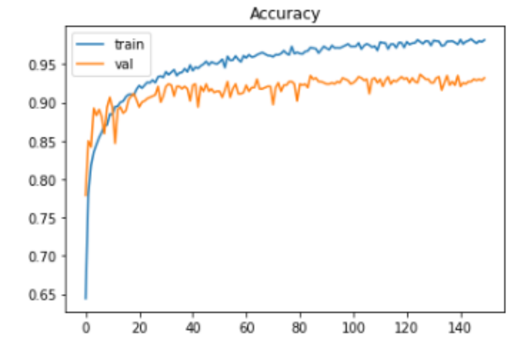

Figure 5. Accuracy Results with a Dropout Value of 0.25

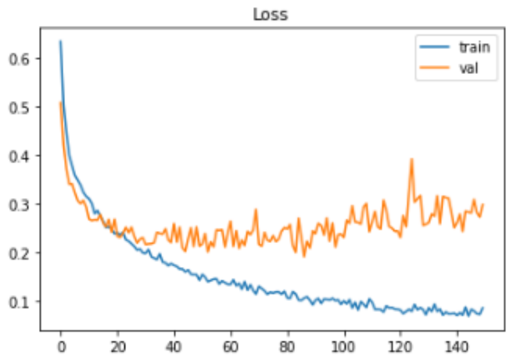

Figure 6. Loss Results with a Dropout Value of 0.3

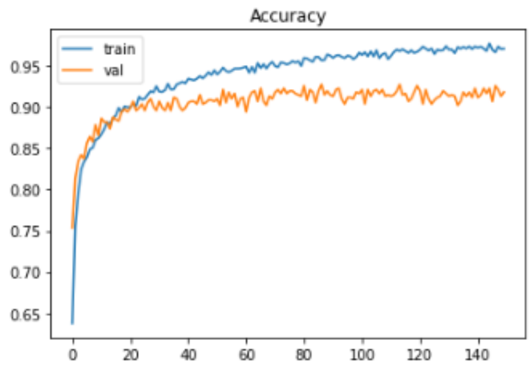

Figure 7. Accuracy Results with a Dropout Value of 0.3

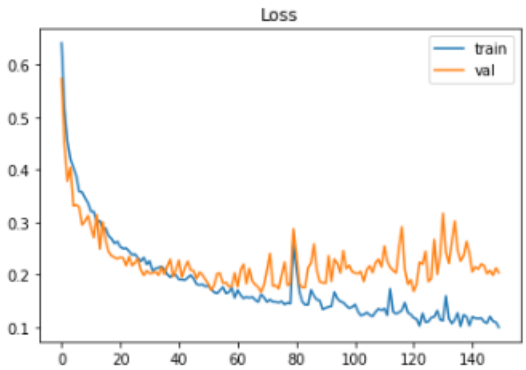

Figure 8. Result of Loss with a Dropout Value of 0.35

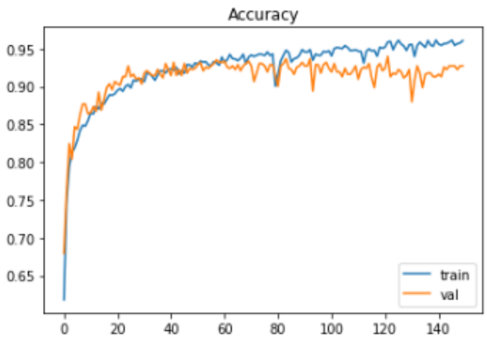

Figure 9. Accuracy Results with a Dropout Value of 0.35

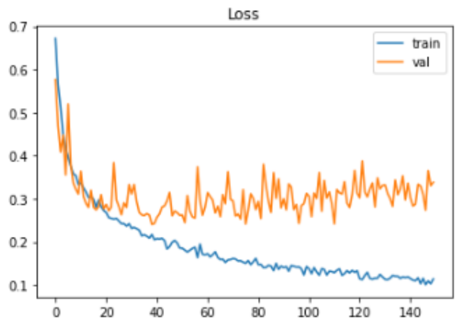

Figure 10. Loss Results with a Dropout Value of 0.4

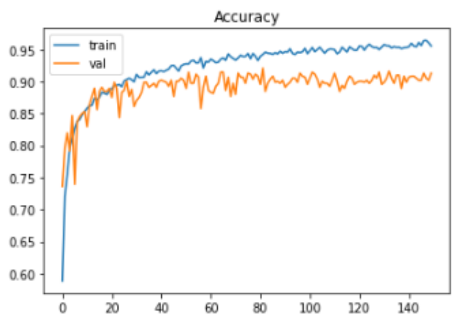

Figure 11. Loss Results with a Dropout Value of 0.4

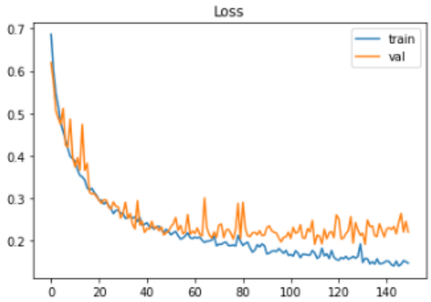

Figure 12. Loss Results with a Dropout Value of 0.45

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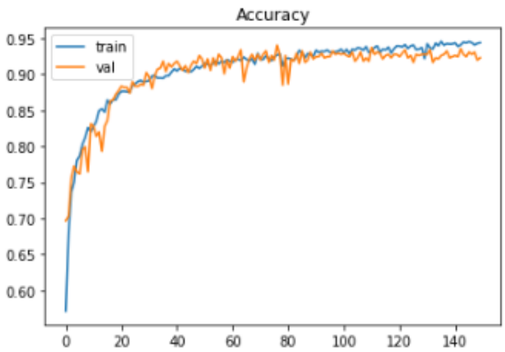

Figure 13. Accuracy Results with a Dropout Value of 0.45

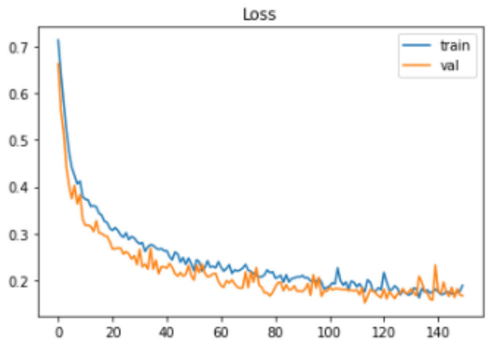

Figure 14. Loss Results with a Dropout Value of 0.5

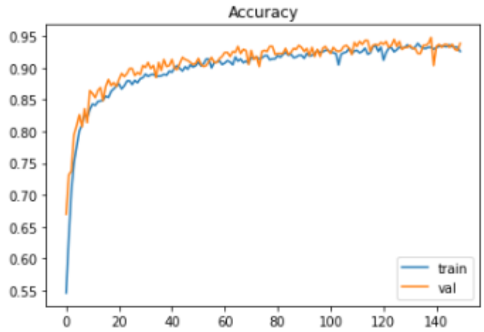

Figure 15. Accuracy Results with a Dropout Value of 0.5

In Figure 2 to Figure 15, you can see changes in loss and accuracy during the training process with dropout values ranging from 0.2 to 0.5. Based on the graph, experiments using a dropout value of 0.5 performed best compared to experiments using dropout values of 0.2 to 0.4. Then after obtaining the best performance of the LSTM model from the training process, the model was tested using test data measuring 10% [18]. The resulting model is used to measure performance using a fusion matrix containing precision, acquisition, precision, and f measurement parameters. Figure 16 shows the resulting fusion matrix.

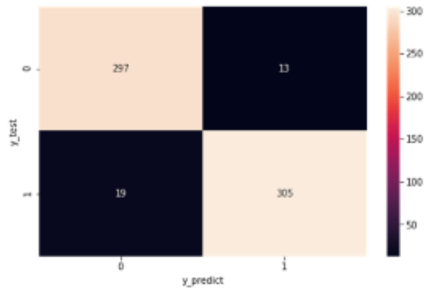

Figure 16. Confusion Matrix

Based on Figure 16, there are a total of 634 test data, 297 of which are predicted to be fake (TP) Hoax test data predicted to be hoaxes when in fact they are not real or hoaxes 19 test data (FP) [19]. Next, there are 305 hoax test data predicted to be genuine or non-hoax (TN), and 13 hoax test data predicted by non-hoax (FN). Thus obtaining precision, recall, precision, and f-measure values of 0.94, 0.96, 0.94, and 0.95.

Next, the study conducted tests using support vector classifier models, logistic regression models, and multinomial Naive Bayes on the same dataset (fake_or_real_news) [23]. The precision, recall, precision, and f values of the support vector classifier model are 0.82, 0.94, 0.87, and 0.95, respectively. The logistic regression model obtained precision, recall, precision, and f-value of 0.92 each, while the naïve

Bayes multinomial model obtained precision, recall, precision, and f-value of 0.92. 0.85, 0.88, 0.88.

4. Conclusion

In this study, LSTM method has been applied to detect fake news. The proposed method is capable of identifying fake news with average precision, recall, accuracy, and f-measure values of 0.94, 0.96, 0.94, and 0.95. The results showed that LSTM provides superior performance compared to the Support Vector Classifier, Logistic Regression, and Multinomial Naive Bayes methods.

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