Comparison of Fake News Detection using Machine Learning and Deep Learning Techniques

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***Abstract*—Fake news has spread widely on the Web in recent years due to the massive amount of information exchanged on digital media. This has motivates our study to determine the best-performing model among two Machine Learning models: Naïve Bayes (NB), Support Vector Machine (SVM), and three Deep Learning models: Long Short-Term Memory (LSTM), Neural Network with Keras (NN-Keras), and Neural Network with TensorFlow (NN-TF). We examined five models using two different English language news datasets. The performance of the models was evaluated using four metrics; accuracy, precision, recall and F1-score. The obtained results showed that deep learning models had achieved better accuracy than traditional ML models. The LSTM model has outperformed all other models examined. It achieved an average accuracy of 94.21%. The NN-Keras has also produced a good performance with an average accuracy of 92.99%. The words' order carries critical information and plays a significant role in the fake news classification, where our LSTM makes a prediction based on this.**

Keywords—Fake news detection, Machine learning, Deep learning techniques, LSTM

I. INTRODUCTION

Fake news is defined as intentionally and verifiably false information published by a news outlet [1], [2]. Nowadays, fake news has become widely spread and has bad effects on many aspects of life, such as political, economic, and education. It is typically generated for commercial interests to attract viewers and collect advertising revenue. According to the statistics, two million accounts worldwide are closed on WhatsApp platform every month to limit the spread of fake news or misinformation [3].

During the coronavirus disease 2019 (COVID-19) pandemic, there was fake news on COVID-19 on social media has been countered. For example, the website https://sebenarnya.my/ has spotted around more than 160 fake news in Malaysia only in March 2020. Producing fake news about the COVID-19 is still continuous. So, identifying fake news in social networks is very important because they have an impact that can be tremendous due to the massive user numbers globally, which is further boosted by the extensive information sharing and propagation among these users.

In an attempt to reveal the fake news due to the increase of false posts or misinformation, several fact-checking websites have been deployed to expose or confirm stories: The most popular websites that expose fake news include snopes.com, factcheck.org, fakenewswatch.com, and politifact.com, etc. Locally, in Malaysia, there is sebenarnya.my by the Malaysian Communications and Multimedia Commission (MCMC). These websites play a crucial role in combating fake news, but they require expert analysis, which inhibits a timely response. As a response, numerous articles and blogs are written to raise public awareness and provide tips on differentiating truth from falsehood. Nowadays, with the advent of digital technology and the increasing amount of information that people access and share every day, this information might be unverified or assumed to be true. Machine learning techniques have become popular in detecting and classifying fake news.

Five machine learning models were compared to identify which model is the best to classify fake news [4]. They found that the best perfoming model was Long Short-Term Memory (LSTM) networks implementation and used a dataset of news articles written in a formal English language.

Based on the literature review, some studies [4, 5] have been conducted to determine which machine learning algorithms are the best to detect fake news. It has achieved good results (high accuracy) when applied to some deep learning models such as LSTM by implementing a dataset [4]. However, these studies still disapproved that these models can be generalized to different news from different sources. So, implementing these models on a different dataset (different topics of news or various news resources) is needed to be applied to approve its effectiveness in different datasets. Moreover, if these models (Naïve Bayes (NB), Support Vector Machine (SVM), and LSTM achieved high accuracy, there is also a need to examine these models with fake news of varied languages. That means there is a need to apply the best model in a different language dataset. Different datasets indicate different news datasets collected from various news sources. It includes thousands of news articles crawled from various websites where various authors write these news articles, and each author or website has its own writing style. Finally, collecting datasets for fake news detection is very important because they can be used again in future work. So, it is necessary to see how does the dataset affect classification performance.

To sum up, our problem is that the previous studies conducted to determine the best approaches for fake news detection were not implemented on different datasets. These studies claimed that some deep learning approaches such as (LSTM and Neural Network (NN)) outperformed some basic machine learning such as (NB and SVM) on detecting fake news but with the implementation of a single dataset, not several datasets. Re-implementation of these studies on several datasets is needed before making any further improvement or changes in those models that have outperformed. This paper aims to compare traditional machine learning models ((Naïve Bayes (NB) and Support Vector Machine (SVM)) with deep learning models (Long Short-Term Memory (LSTM), Neural Network with Keras (NN-Keras), and Neural Network with TensorFlow (NN-TF)) using two different datasets of news articles.

This paper consists of five (5) sections. Section I discuss the background of this study, including the definition of fake news. Section II discusses the related works, Section III

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introduces the methodology used in the study, and Section IV presents the results of the work and discussion. Lastly, section V concludes the paper with a summary of the findings and recommended future work.

II. Related Works

NB approach was implemented on Facebook news posts where classification accuracy achieved was around 74% [6]. The dataset used was BuzzFeed News dataset which is collected from nine Facebook pages. The size of the dataset was 2282 posts. NB used bag of words features in this study as a method of feature extraction. Most of the studies use NB as a baseline for their work because it is easy to implement, fast, and can outperform the more powerful alternatives, especially for small sample sizes.

A hybrid deep learning model of LSTM and CNN models was proposed by [7] to detect and classify fake news from Twitter posts. The dataset used in that study was consisted of around 5800 tweets. Using deep learning models enables automatic feature extraction. Embedding layer was used where the tweets cleaned and prepared such that each word is one-hot encoded. The proposed work using this deep learning approach achieves 80% accuracy. Using deep learning models gives better results than using traditional machine learning models due to the advantages the deep learning approaches have such as memory and hidden layers.

Five learning models: NB, SVM, LSTM, NN-TensorFlow and NN-Keras have been implemented using a corpus of labelled real and fake news articles to build a classifier that can make decisions about information based on the content of news articles from the corpus. The Doc2Vec embeddings has been used in all models applied by this study [4] to generate feature vector of each article; except LTSM model for which the text encoding and word embedding is used. The dataset used in that study [4] was crawled from Kaggle [8]. According to a quick look at the dataset, the majority of articles that this dataset contains were about political news. It has total news around 20K records (articles). 10K articles of it were real news, and 10K of it were fake news as well. A full training dataset has the following attributes: id, title, author, text, and label (1 for unreliable; and 0 for reliable).

LSTM gave the best results and achieved high accuracy and F1-Score in comparison to all other models using text classification approaches [4]. NN-Keras has also achieved a high accuracy after LSTM. The reason that makes LSTM performs well is that the text is inherently a serialized object. And most models use the Doc2Vec to get their feature vectors and hence, they rely on the Doc2Vec to extract the order information and perform classification on it. Moreover, the LSTM model preserves the order of words using a different pre-processing method and makes a prediction based on both the words and their order.

Four basic machine learning models are been examined; Random Forest, XGBoost, NB, and Logistic Regression to detect or classify fake news articles [9]. The dataset used in that study [9] was the same Dataset 1 used in this project where this dataset was published on Kaggle. The real news articles were collected from various publications such as the New York Times, Washington Post. The fake news articles were collected from 244 unreliable sources and then were identified and reported as fake by BS Detector. Each model was tested against the header and content of the articles. The standard Term Frequency-Inverted Document Frequency (TF-IDF) method and google word2vec were used as the vectorization technique in this study to represent data. The vectors obtained from Google's Word2Vec word embeddings were inputs to train the models that have been examined in this study. This study showed that using word2vec as vectorization to represent data was significantly improved accuracy for most of the models used in the study.

A model for fake news detection with two different feature extraction techniques and six machine learning models have been examined, Stochastic Gradient Descent (SGD), SVM, Linear SVM (LSVM), K-Nearest Neighbour (KNN), Decision Trees (DT) and Logistic regression (LR) [10]. The dataset used was a new dataset collected by their team by compiling publicly available news article on Kaggle. The dataset used consists of 12,600 fake news, and 12,600 truthful articles. The results showed that the Linear SVM model achieved an accuracy of 92%, and TF-IDF outperformed Term Frequency (TF) using two different datasets.

Neural network models were applied with two types of word vectors, N-gram vectorization and sequence vectorization [3]. These models are trained on title news and content news to detect fake news. US English news dataset is collected and combined from two different Kaggle sources such that both of them are having similar attributes of news title, news content, and news labels ("0" for real news and "1" for fake news). The dataset used was containing a total of 9,805 articles; fake and real. The study showed that training model with N-gram vectorization was performing better than training with sequence vectorization. Models trained with N-gram vectors on news content achieved the best accuracy and recall with 90.3% and 97.50% respectively. The study above [3] showed the NN-Keras produced better but does not address other deep learning models such as LSTM model which achieved better accuracy than NN-Keras model as in some studies reviewed above [4].

A fake news detection method has combined two deep learning models, LSTM and Gated Recurrent Unit (GRU), with several word vector representations [11]. The models also combined with online data mining, which works as additional features to the dataset. George McIntires Fake News Dataset was chosen for the testing. It has 10,558 rows(entries) where it includes fake news and real news in 1:1 ratio. LSTM model achieved better performance with an accuracy of 94% when additional online data are combined with the model. As seen in this study, the suitable word vectorization for the LSTM model was word2vec, which used in similar studies[4], [9]. The LSTM model showed better-performing in terms of precision, recall, and F1-Score for detecting fake news in this study.

A comparison of three machine learning models which are SVM, NB, and Logistic Regression was conducted to classify fake news [12]. Two datasets were used in their study, the ISOT dataset with a size of 31K news articles and the Liar Liar dataset with a size of 12.8K news articles. For the extraction of features, TF and TF-IDF were used, where the features play a main role in the detection of fake news. In that study, the models' comparison results showed that the Naïve Bayes had achieved better accuracy for the TF feature. Logistic Regression has also produced better accuracy with TF-IDF. Additionally, due to the big size of the ISOT dataset comparing with the Liar Liar dataset, the ISOT dataset gave better results than the Liar Liar dataset.

A method was suggested to predict fake news by combining deep learning models with different metadata of news articles such as text, title, and author [13]. It used the word embedding technique with convolutional neural networks (CNNs). The study tested three models: CNN (Text only), CNNs (Text+Title), and CNNs (Text+Author). The last model, CNNs (Text+Author), achieved the best accuracy among the other models examined in this study with an accuracy of 96.00%. They implemented a single dataset proposed by kaggle.com, containing 20K news articles; 10K are fake articles, and 10K are real articles [13].

Based on the literature reviewed above, several datasets are used to examine different machine learning and deep learning models. The common datasets used in these studies reviewed above are datasets that are crawled from Kaggle. These datasets are most contains full news articles. Five studies [3], [4], [9], [10], [13] used Kaggle datasets.

The common methods used in the studies reviewed above are both machine learning and deep learning methods. NB and SVM is an example of machine learning models that widely used in studies. Recently, these methods are used as a baseline for the work. As reviewed, NB used in [4], [6], [9], [12], [14]. In some studies, NB did not achieve better results, but it used at least as a baseline. Thus; it was recommended to used NB in our work. On the other hand, The common method used which achieved better results is the LSTM model and NN-Keras. In [4], LSTM model achieved the best accuracy, and NN-Keras models achieved competitive results. LSTMs can keep the "Short Term Memories" for "Longer" since there are different gates - input, output and forget to control the information flow. That makes LSTM is suitable for our work. In [7], the LSTM model outperformed CNN model, but the dataset used was short texts with 5,800 tweets.

Additionally, most of the studies reviewed above have used different methods to extract the text news features. The popular methods used to extract features from the text news articles which are used in studies reviewed above are, bag of words, one-hot encoding, TF, TF-IDF, word2vec and Doc2Vec for word embeddings. Among these features, it can be noted that using word2vec as a vectorization technique has outperformed using the standard TF-IDF method [9], and TF-IDF has outperformed TF [10]. In this work, only two features were used, word2vec and Doc2Vec, as previous studies showed that they produce better results when used with machine learning and deep learning models. Due to word2vec adds meaning to words, it is recommended to use word2vec as a vectorization technique to improve the accuracy of models.

III. METHODOLOGY

A. *Experimental Design*

The research design that has been followed in this study is provided in this section. By applying these steps, the study objectives have been achieved. The three main phases of this study that have been taken are Dataset preparation (Phase 1), Implementation (Phase 2) and Evaluation (Phase 3).

B. *Dataset Description*

1) Dataset 1: The first dataset (Dataset 1) was drawn from many different news sources. The sources are around 250 websites and blogs. These sources are companies' names that published the article news. For example, the real news was published by Washington Post, Reuters, Guardian and Cable News Network (CNN) news network, where the fake news was published in companies' websites such as 100percentfedup, 21st centurywire and activist post. It is available on the Kaggle website [15]. The dataset's size is around 27K articles: 12K of it are fake article news, and the other 15K are real article news. Each article has the following columns: Title: the title of the article, Content: the article's text, Publication: which company published this article, and Label: real or fake.

2) Dataset 2: The (Dataset 2) used in this project was collected by the Information Security and Object Technology (ISOT) research group, which is known as ISOT dataset [16]. The dataset contains two types of articles, fake and real news. This dataset was collected from real-world sources; the truthful articles were obtained by crawling articles from reuters.com (News website). As for the fake news articles, they were collected from different sources. The fake news articles were collected from unreliable websites that were flagged by politifact.com (a fact-checking organization in the USA) and Wikipedia. The dataset contains different types of articles on various topics; however, the majority of articles focus on political and world news topics. In this paper, only politics news type (for real) and politics type (for fake) were selected to be our dataset. The overall number of article news that has been selected was 18113 articles.

3) Preprocessing Datasets: Before presenting our dataset to the source code, a little bit of preprocessing on the data have been done to train our models. The preprocesses include: Data cleaning, Inconsistent data representation, Missing data handling (removing missing values in the data), Removing the repeated instances (duplicated records) and removing the articles that are not crawled or represented in the file correctly. After preprocessing the datasets, we have obtained cleaned datasets that are now ready for processing. Table I, and Table II give a summary of instances number in our datasets; Dataset 1, and Dataset 2; before and after, the preprocessing respectively.

TABLE I. DATASET 1 BEFORE AND AFTER PREPROCESSING

Dataset	Before preprocessing	After preprocessing
Real articles	15,712	15,607
Fake articles	12,999	12,738
Total	28,711	28,345

TABLE II. DATASET 2 BEFORE AND AFTER PREPROCESSING

Dataset	Before preprocessing	After preprocessing
Real articles	11,272	11,271
Fake articles	6,841	6,430
Total	18,113	17,701

C. *Classification Models*

Five models have been selected. This study is conducted to compare the results obtained using several datasets with the study results [4], which used five classification models so, NB, SVM, NN-Keras, NN-TensorFlow, and LSTM have been used in this study. We implemented the classification using these models with the same parameters used in that study [4] to ensure there is no bias when we compare our results with the results obtained by [4]. The experiment of this study implemented five times for each model due to some models use random parameters.

1) Naïve Bayes (NB): NB is used in this project as it is a popular baseline model used in research related to classification problems. The embeddings used for NB here are generated using the Doc2Vec model. The goal is to produce a vector representation of each article. After preprocessing the text news articles, a list of words has produced, which can be input into the Doc2Vec algorithm to produce a 300-length embedding vector for each article. Table III shows the parameters used in NB model.

TABLE III. PARAMETERS USED FOR NB

Parameters	Embeddings	Size of input vector	Implementation
Values	Doc2Vec	300	(GaussianNB)

2) Support Vector Machine (SVM): SVM is one of the most used techniques in classification problems such as text classification (fake news detection). Using kernel trick in SVM makes it to give good results in the classification problems. In this paper, Doc2Vec is implemented to which generates vector representations for words for our SVM model. The Radial Basis Function kernel has been used. Two Doc2Vec feature vectors will be close to each other if their corresponding documents are similar, so the distance computed by this common kernel function should still represent the original distance. Table IV shows the parameters used in SVM model.

TABLE IV. PARAMETERS USED FOR SVM

Parameters	Embeddings	Size of input vector	Kernel
Values	Doc2Vec	300	Radial Basis

3) Neural Networks - Keras : A feed-forward neural network model has been implemented in this study using Keras. Nowadays, neural networks are used widely in Natural Language Processing (NLP) applications. To present the news article to our model, Doc2Vec has been used to generate a 300-length embedding vector for each news article. Three hidden layers have been used in this implementation. The first and second layer used 256 neutrons for each. The third layer used 80 neutrons. These layers are interspersed with dropout layers to avoid overfitting. The activation function used here is the Rectified Linear Unit (ReLU), which most deep networks use it. ReLU has been found to train faster and have less expensive operations when compared to sigmoid/ tanh. Table V shows the parameters used in NN-Keras model.

TABLE V. PARAMETERS USED FOR NN-KERAS

Parameters	Values
Embeddings	Doc2Vec with 300-length input vector
Length of 1st hidden layer	256 neutrons
Length of 2nd hidden layer	256 neutrons
Length of 3rd hidden layer	80 neutrons
Activation function	ReLU
Learning rate	0.01
Training steps	10000
Size of input vector	300

4) Neural Networks – TensorFlow: The neural network model has been implemented in this study using TensorFlow. The same implementation of the previous model (using Keras) has also been done here with simple differences. Doc2Vec has been used to generate a 300-length embedding vector for each news article to be an input for our model. Three hidden layers have been used in this implementation. All layers had 300 neutrons for each. The activation function used here is the ReLU. Table VI shows the parameters used in NN-TensorFlow model.

TABLE VI. PARAMETERS USED FOR NN-TENSORFLOW

Parameters	Values
Embeddings	Doc2Vec with 300-length input vector
Length of 1st hidden layer	300 neutrons
Length of 2nd hidden layer	300 neutrons
Length of 3rd hidden layer	300 neutrons
Activation function	ReLU
Learning rate	0.001
Training steps	20000
Size of input vector	300

5) Long Short-Term Memory (LSTM): Since the order of words is important in our model (LSTM), the Doc2Vec cannot be used or not suitable here because it will convert the entire document to one vector, and thus; the information of words order will be lost. So, word embedding will be used instead. After doing the preprocesses like removing special characters from text and preparing our text for processing, the frequency of each word in our dataset has counted. Then, the 5000 most common words have been found and given each one a unique integer ID. For example, the most common word had ID 0, and the second most common one had 1, and so on. The 5000 common words that have been chosen cover most of the text. After that, each common word has been replaced with its assigned ID and deleted all uncommon words.

Since the LSTM model requires a fixed input vector length, the list longer than 500 numbers was truncated. For those lists shorter than 500 words, 0's have been put at the beginning of the list. The data with only a few words have been deleted since they do not carry enough information for training. By doing this, the original text string had been transferred to a fixed-length integer vector while preserving the words order information. Finally, word embedding has been used to transfer each word ID to a 32-dimensional vector. The word embedding will train each word vector based on word similarity. If two words frequently appear together in the text, they are thought to be more similar, and the distance of their corresponding vectors is small. Table VII shows the parameters used in LSTM model.

TABLE VII. PARAMETERS USED FOR LSTM

Parameters	Values
Embeddings	Word2Vec
Embedding Vector Length	32
Activation function	sigmoid
Batch size	64
Epoch number	5
Size of input vector	500

D. Evaluation Metrics

Four metrics have been selected, which are accuracy, precision, recall and F1-score to provide a comparison of performance between the models used in this study.

1) Accuracy: Accuracy measure is mostly used in machine learning to evaluate the performance of classification models. It tells how well the classifier correctly identifies an instance of the dataset, or as a percentage of the total number of predictions that are true.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

2) Precision: Sometimes, classification accuracy is not enough to measure the performance of the models. So, more performance measure is needed to evaluate our models. Precision is one of these metrics that can be used to measure the performance of the models. It is defined as the number of correctly classified positive examples divided by the number of examples labelled by the model.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

3) Recall: Recall or sometimes known as sensitivity defines as the number of correctly classified positive examples divided by the number of positive examples in the data:

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

4) F1-Score: F1-Score is one of the common evaluation metrics used in text classification problems. It is the harmonic mean between precision and recall. Thus, it balances between precision and recall. It tells you how precise your classifier is (how many instances it classifies correctly), as well as how robust it is (it does not miss a significant number of instances). Mathematically, it can be calculated in terms of confusion matrix by using the following equation:

$$F1 = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (4)$$

IV. Results and Discussion

The experiment was performed on the (Dataset 1) and (Dataset 2). The results of the implementation of five machine learning algorithms using these datasets were stated in Fig. 1. These results are the average of five times of implementation as it is explained in the previous section.

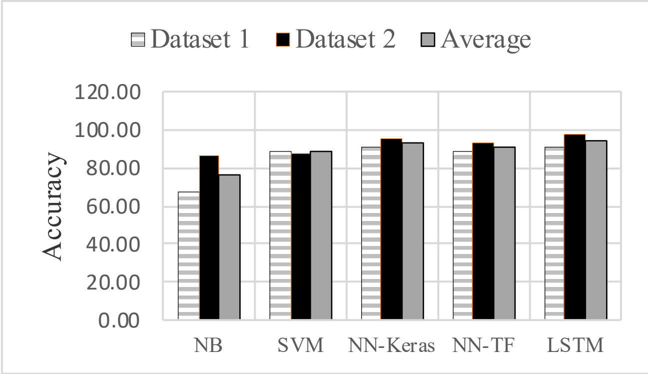

Fig. 1. Average of accuracy for our models

Fig. 1 shows the performance of the five models used on Dataset 1 and Dataset 2. It is worth noting that LSTM outperformed all other models in terms of accuracy, precision, recall and F1-Score. LSTM achieved an average accuracy of 94.21%, and NN-Keras has been showing good classification performance where it achieved an average accuracy of 91.33%. LSTM has achieved better results than other models due to it classifies the text depending on the words and its order. So, more features are extracted that LSTM classifies the text based on them. Considering the word order makes LSTM achieves higher accuracy than others.

In contrast, NB model produced the lowest accuracy among the models examined in this study using Dataset 1 and Dataset 2 because NB Cannot incorporate feature interactions and the predictors/features are independent. In general, the deep machine learning models, LSTM, NN-Keras and NN-TensorFlow have produced better classification performance than traditional machine learning, NB and SVM.

By comparing our results with the results obtained by [4], it is noted that the LSTM model is the best in comparison to all other models, NB, SVM, NN-Keras, NN-TF, for detecting fake news as shown in Table VIII. As mentioned in the reviewed studies above, all studies, including this study, agreed that the LSTM model had been outperformed all others. So, it is highly recommended for future studies to conduct more improvement on the LSTM model to detect fake news where it was examined by several studies and approved itself as the best classifier for fake news. This clearly states the most important finding of this study, which is that the LSTM model is the best performing model out of the models, NB, SVM, LSTM, NN-Keras, and NN-TF in fake news detection.

TABLE VIII. Comparison of Our Results with Results of Previous Researches

Study	Performance Measurements	Machine Learning Models				
		NB	*SVM*	*NN-Keras*	*NN-TF*	*LSTM*
Current study using Dataset 1	Accuracy	67.12	88.83	91.02	89.06	91.31
Current study using Dataset 2		86.50	87.68	94.96	93.60	97.11
Curci et al. (2018)		71.68	88.23	92.66	90.83	94.58
Current study using Dataset 1	Precision	68.68	88.67	90.94	89.04	91.43
Current study using Dataset 2		85.48	87.77	94.87	93.22	97.36
Curci et al. (2018)		73.31	88.70	92.66	90.82	94.58
Current study using Dataset 1	Recall	68.27	89.00	90.93	88.83	91.16
Current study using Dataset 2		85.17	85.47	94.25	92.92	96.44
Curci et al. (2018)		71.48	88.15	92.66	90.83	94.58
Current study using Dataset 1	F1-Score	67.07	88.76	90.93	88.91	91.19
Current study using Dataset 2		85.32	86.07	94.53	93.07	96.83
Curci et al. (2018)		71.05	88.17	92.65	90.82	94.58

All classification models except SVM model had achieved a higher accuracy when Dataset 2 was used, and they achieved a little bit lower accuracy when Dataset 1 was used comparing to Dataset 1 and also comparing to the dataset that has been used by [4]. One of the possible explanations of outperforming models when Dataset 2 was applied is that the nature of Dataset 2 has trained our models well. This means that the models are trained well when Dataset 2 has used. Dataset 2 is containing news articles from variety sources. Each source has its own writing style. So, the training process of models might not get enough data on training for each writing style. For example, Dataset 1 was drawn from different news sources which are more than 250 websites. In Dataset 2, the true news had been crawled from one source, which is reuters.com (website news). The number of articles for each source of the 250 websites in Dataset 1 definitely will not equal the number of articles that are obtained from once source (reuters.com) in Dataset 2. This explains that the news articles of reuters.com (real news article) which are in Dataset 2 have trained well the classification models because they are enough number of articles whereas the number of news articles for each source of the 250 which are in Dataset 1 is limited in training.

Besides, when comparing [4] with results in Dataset 1, it is noted that the performance of models when using [4] dataset was higher than using Dataset 1 for all metrics used, Accuracy, precision, recall and F1-Score. This is because Dataset 1 has news articles from several sources that reach more than 250 news sources. So, each news source in Dataset 1 may bring a few news articles and hence; the writing styles in Dataset 1 are varied. Therefore; the training models was not well due to the few data or a smaller number of news articles for each style. Although the instances of Dataset 1 are 27K, which are more compared to [4] dataset, but the Dataset 1 is a little bit skewed where it contains 12K fake articles and 15K real articles in Dataset 1. In [4] dataset, 10K fake article and 10K real articles are included. This might be contributed to make [4] dataset get better results than Dataset 1.

V. Conclusion

The fake news is become nowadays more spread on the Web. Detection fake news automatically is needed especially with the advent of technology and increasing of the amount of news data on social media platforms and spreading this fake news quickly. With using machine learning techniques which achieved good results in classification problems, fake news detection is one of these problems where a lot of researches applied machine learning techniques to solve this type of problems. This study aims to provide a comparison between five learning models to determine the best model for fake news detection. The classification models are NB, SVM, NN-Keras, NN-TensorFlow and LSTM. A pre-processing on our dataset has been conducted to prepare them for the processing. The implementation phase applied to classify news articles into fake or real using the datasets prepared previously. The evaluation of the models has been implemented at the end, followed by comparing the obtained results with the results of previous studies. The results obtained showed that deep learning models like LSTM, NN-Keras and NN-TensorFlow outperformed traditional machine learning models like NB and SVM. LSTM classifier provides the best results among the other deep learning. This finding agreed with the previous studies that showed the outperforming of LSTM model in the classification of fake news. In the future, it is recommended to re-apply this study with different datasets with different languages of news such as Malay news or Arabic news. In this case, the suitable tools for cleaning datasets such as removing stop words should be considered.

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