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Fake News Detection Using NLP with LSTM

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Abstract—*Fake news on social media and various other media is spreading widely and has received serious attention due to its ability to cause massive social and national damage with devastating effects in this digital era. The explosive growth of social media platforms has not only significantly improved the availability of information but also accelerated the spread of fake news. The spread of fake news poses a serious threat to public trust in the media. This is a complex issue that requires the detection, investigation, and management of fake news. There is an existence of another approach to addressing this issue, however, many potential methods and techniques remain unexplored. Previous literature has dominantly used LSTM for fake news detection neglecting the possibility of NLP. Therefore, this study proposes a combination of Natural Language Processing (NLP) and long short-term memory (LSTM) in detection of fake news. The result from the experiment demonstrates that our techniques achieve a higher rate of detection.*

Keywords— *Fake news detection, natural language processing, long short-term memory, detection, devastating effects.*

I. INTRODUCTION

In 21st century, social media has taken the place of traditional way of dissemination of information (Shu et al., 2016). It not only offers opportunity for people to connect and exchange factual information but drives the speed of consumption of fake news (Shu et al., 2016). Fake news is information that is verifiably false and intended to mislead people (Allcott & Gentzkow, 2017). Fake news has received significant attention due to its potential to cause enormous social and national damage (Allcott & Gentzkow, 2017). As the digital world continues to grow, the more we become dependent on our source of information, which we incline to get a lot of fake news that is widespread with the masses following it without any prior or complete information about the event's authenticity (Shu et al., 2019). Today, more of our social activities have been shifted from staged to online leading to double the growth of digital news. Fake news has created a threat to the security, economy, prosperity, and identity of the country. Billions of articles, texts, or blogs are created on the internet as the clock goes by, and with a click, the news reaches many without authenticity. Without control gates to prevent the radical spread of fake news, simple actions become a serious problem.

In Malaysia, there is a party Anti-Fake News Act (AFNA) introduce by the government that indicates that fake news stories can be interpreted in the pattern of features, audio, visual, or any from social media applications capable of suggesting ideas or words (Hassan, 2019). To mention a few social media applications available in the market, “Facebook”, “WhatsApp”, “Twitter”, etc.

Considering WhatsApp as an example, referring to the statistics computed, there was a total of 2 million accounts being closed every month by preventing the spread of fake news (Allcott & Gentzkow, 2017; Rosenfeld et al., 2020). In addition, it is not just in touch with friends and family but also part of politics. In 2018, Brazilian has poison by fake news via WhatsApp. The reason was that a total of 44% of Brazilian voters use WhatsApp to know about their country's political and electronic information (Anthony Boadle, 2018). Owners of these social media applications spend efforts and a huge sum of money to develop an automated process to deal with the spread of fake news.

Indeed, there is the existence of some approaches to addressing this issue, however, many potential methods and techniques remain unexplored due to limited literature access to the problem of fake news detection. The application of deep learning (Abbas et al., 2022) is one of them. Discourse segment structure analysis has also been used in this domain (Anmol Uppal, 2020), where the use of discourse level analysis for deception detection of news documents to make a hierarchical structure. Techniques by (Shu et al., 2019), where the combination of statistical mining with the evaluation of interpersonal business ventures. The application of SVM and Random Forest has also contributed to this area. The main purpose of this paper is to review the research related to fake news detection and propose and apply our automated deception detection method, which is Natural Language Processing (NLP) with Long short-term memory (LSTM).

Organization. We detail the rest of our paper in the following sections: Section 2 comprises the background and problem statement needed in the later sections. Follow by Section 3, where we present and discuss our proposed methodology. In Section 4, we illustrate the results in a virtual form and finally the conclusion in Section 5.

II. BACKGROUND STUDY

Depending on how people perceive the news that come to them, its sometimes difficult to just conclude whether news article is fake or real. News articles can be divided into various categories. Any information that appears to be misleading the public which can cause any damage can be consider as fake (Rubin & Lukoianova, 2015). Considering fake news detection based on the perspective of fake news via its main models.

A. News Content Model
B. Social Context Model

Fake news can be detected by content presented in articles or by social media metadata carried when published and

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distributed online. There are several approaches that can be applied to any of the above detection models.

A. News Content Model

This style of fake news detection sounds mostly manual and handle real fact-checking of the news conveyed in the article. The main purpose of knowledge-based detection is to do fact-checking in two ways - traditional fact-checking and automation fact check. This is designed to assess the veracity of news by comparing knowledge extracted from news articles validate with actual events.

Manual or traditional fact checking can come from two sources. Peer review and crowdsourced fact checking. Expert validation is mainly performed by a small group of trusted fact checkers such as PolitiFact (The Poynter Institute, 2018), Factcheck (A Project of The Annenberg Public Policy Center of the University of Pennsylvania, n.d.) and many others. gives accurate results. It's expensive and doesn't scale Handle large volumes of incoming news traffic. to another Practical Crowdsourcing Fact Checking Depends on Participation A large number of people act as fact-checkers. Crowdsourced fact checking is more scalable than expert fact checking. Fact checking, but less believable and accurate due to bias Fact checkers tend to favor one side or the other.

Automated fact checking can handle large volumes the amount of information to be reviewed depends largely on the zinformation search, natural language processing, and to some extent Network theory. Functional fact-checking is divided into two phases, creating comparisons of knowledge and experience. Knowledge here means location information such as attributes that have been removed from knowledge.

B. Social Context Model

Communication and sharing features on social media platforms provide additional information, such as social posts in analytics, allowing the discovery of fake news to be compressed from multiple different angles. Similarly, social activities that can provide descriptive data (such as comments) to readers to receive news can be identified in two ways, based on both publication and credibility. Diffusion-based technologies are designed to identify the relationships between the many news published on social media and track them down to the original news. Trust-based technologies use relationships between news articles and other components such as users, publishers, and publications. For instance, news published by unreliable websites or redirected by unreliable users can become fake news from reputable and trusted users. Fake news can be identified by the following authentic parts of the published material: title, claim, source, and disseminator.

III. PROBLEM STATEMENT

Social media is now a source of communication and information, respectively. But, if so, how do we measure quality and safety? This should remind us of danger. The internet is intertwined with everyday life, and people have turned social media apps into an integral part of their lives. The use of social media diversity continues to grow, and advanced technology has made the world local. A world where people can freely communicate with anyone from different part of the world. The exposure of the digital world to us has enhances the possibilities for hacker and strangers to access our vital information without barriers. We strongly believe that, social networks have a huge impact that can affect interpersonal communication and relationships, where people are actively committed to them and allow social media to dominate their way of life.

The impact of fake news and rumors is causing serious harm to individuals, families and countries as a whole. Suicide is an extreme case due to the spread of fake news, and we must therefore address this problem with the resources available. The existing system on the topics of deep learning for deception and fake news detection has been focusing on online reviews and publicly posting on social media. Fake news is harder to spot because it can work in different paradigms, and there has been a huge leap within NLP.

IV. PROPOSED METHODOLOGY

In order to avoid the spread of misinformation and fake news, the detection of fake news is very necessary, which this project provides. We solved our problem by applying natural language processing (NLP) with long short-term memory. The diagram below shows the structure of the method.

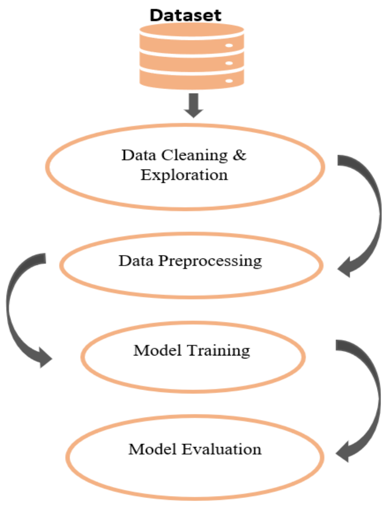

Fig. 1. Proposed Workflow Methodology

- From the diagram, embedding_input set each value in the input array to a vector of a defined size. The weights in this layer are then learned which will be needed during the training process before initialization takes place.
- Followed by the embedding stage, where low-dimensional space is translated into high-dimensional vectors.
- Moving on to dropout stage. As the name implies, a method where randomly selected neurons are left out during training process. This means that their involvement in activating downstream neurons is temporarily eliminated on the forward pass, and any weight updates are not applied to the neuron on the backward pass.

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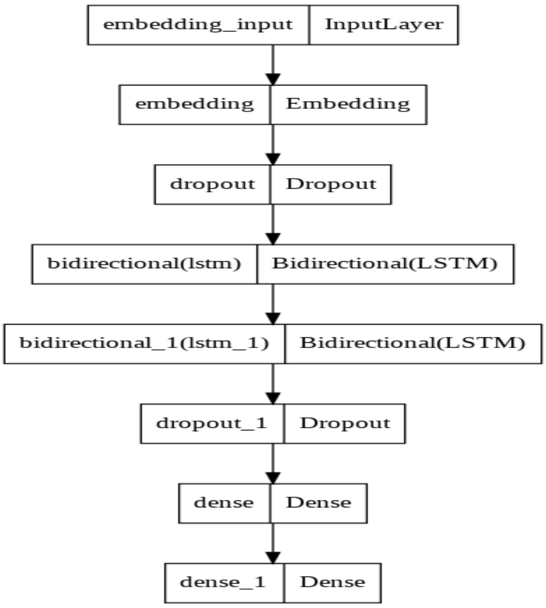

Fig. 2. LSTM Model Description

- In bidirectional, our input flows in two directions, that is why it is termed BI-LSTM. Are the techniques of making any neural network o have the sequence information in both directions which is the future to past or the past to future.
- The dense section is the frequently used layer, mostly a connected neural network layer. This is very important because it can change the dimensions of the vector. Dense layer does the operation on the input and return the output.

A. *Data Gathering*

Data gathering is one of the most important parts of building our models. Because no matter how well designed our model might be, it will not learn anything useful if the training data is invalid. News datasets can be collected from different source which may include University of Victoria, Kaggle and others. On the other hand, we are not interested in the news sources but rather focuses on training our model to be able to classify whether is fake or real considering the title and the content. In this paper, our dataset used are ISOT Fake News and Fake or Real News which was collected from University of Victoria and Kaggle respectively. The dataset we used contains attributes of news title, news content and news label of 0 for real news and 1 for fake news.

B. *Data Cleaning and Exploration*

To get our collected dataset ready for exploration, we have to go through the filtration process. In addition to deleting identifiers and URL columns, all blank, duplicate, and errors rows are also deleted. The error rows are also removed because some news headlines or content have characters such as hashtags ("#") or tabs ("t") making the data unclean enough to work with.

Data exploration is used to understand features and find data patterns. In addition, studying the data can help minimize the risk of extreme data imbalances, which can greatly affect the models trained later. Data exploration is practiced to show the distribution of fake news and real news, word counts or build a cloud of words to show the most commonly used words.

C. *Data Processing*

Data preparation is a process where the data is being prepared and convert into a context in which the machine can understand and then feed into the model to be trained (Swasti Singhal, 2013). Traditionally, this has been an important initial step in the data mining process. Pre-processing of data converts data into easier and more efficient processing formats in data mining, machine learning and other data science tasks. These techniques are often used in the early stages of deep learning. In NLP, the preprocessing of text is the first step in building a model, where basic stages like tokenization, lower casing, stop words removal, stemming and lemmatization plays a role.

In our case, we are dealing with news headlines and content, so we use Keras which provide the function one_hot to efficiently encode each word in the headlines as an integer. This is done prior to one_hot encode or word embedding. Like Keras, deep learning models require that all input and output variables be numeric. Meaning, if our data contains categorical data, it must be encoded into numbers. Henceforth, we checked and make all sentence of the data of same length, by using pad_sequences to ensure that all sequences in a list have the same length. By default, this is done by padding '0' in the beginning of each sequence until each sequence has the same length as the longest sequence.

Finally, we create a sequential model incrementally via the add() method, the input of the LSTM is always a 3D array (batch_size, time_steps, units) The output of the LSTM can be a 2D array or 3D array, which is depending on the return_sequence argument. If return_sequence is False, then the output is an automatically a 2D array. (batch size, units) Also, if return_sequence is True, the output is a 3D array. (batch size, time_steps, units) in this case; the return_sequence is false - this is the default, therefore - 2D LSTM output.

D. *Model Training*

Model training is a stage of the data science development lifecycle where experts try to find the best combination of weights and offsets for a machine learning algorithm to reduce the loss function across the entire predicted range. In view of detecting and classifying the fake news from the real news, our project would also improve upon some good existing researches. After training our model, it was seen that, it performed well compared to some projects which be later seen.

The Keras neural network model is built with a number of dense layers and trained using a TensorFlow framework to perform the classification task of detecting fake news. In the Keras neural network model, sigmoid was chosen as the activation function, this is important when working with large networks with a large number of neurons and can significantly reduce training and assessment time.

Furthermore, we checked the performance of the classification model by making sure that sure that 'acc' and 'val_acc' and final 'accuracy' are closer to each other. It is normal for validation accuracy to be lower than accuracy. But ideally, these values should be kept similar range. If validation accuracy is much lower than accuracy, be cautious of over fitting.

E. Model Evaluation

Now that the most parts are done, from data collection through the necessary stages to model training, it was now tested on unseen data with metrics of loss, accuracy and computational time. Further classification report was checked for precision, recall and F1 score.

V. Results and Discussion

The figures below show the content of the collected dataset, we then clean it leaving the needed attribute that enable us for further exploration.

	title	text	subject	date	target
0	As U.S. budget fight looms, Republicans flip t...	WASHINGTON (Reuters) - The head of a conservat...	politicsNews	December 31, 2017	0
1	U.S. military to accept transgender recruits o...	WASHINGTON (Reuters) - Transgender people will...	politicsNews	December 29, 2017	0
2	Senior U.S. Republican senator: 'Let Mr. Muell...	WASHINGTON (Reuters) - The special counsel inv...	politicsNews	December 31, 2017	0
3	FBI Russia probe helped by Australian diplomat...	WASHINGTON (Reuters) - Trump campaign adviser ...	politicsNews	December 30, 2017	0
4	Trump wants Postal Service to charge 'much mor...	SEATTLE/WASHINGTON (Reuters) - President Donal...	politicsNews	December 29, 2017	0
5	White House, Congress prepare for talks on spe...	WEST PALM BEACH, Fla./WASHINGTON (Reuters) - T...	politicsNews	December 29, 2017	0
6	Trump says Russia probe will be fair, but time...	WEST PALM BEACH, Fla (Reuters) - President Don...	politicsNews	December 29, 2017	0
7	Factbox: Trump on Twitter (Dec 29) - Approval ...	The following statements were posted to the ve...	politicsNews	December 29, 2017	0
8	Trump on Twitter (Dec 28) - Global Warming	The following statements were posted to the ve...	politicsNews	December 29, 2017	0
9	Alabama official to certify Senator-elect Jone...	WASHINGTON (Reuters) - Alabama Secretary of St...	politicsNews	December 28, 2017	0

Fig. 3. Collected and Cleaned News Dataset

The next stage to data cleaning is data exploration, As the data set criteria must first be checked to see if the data set is unstructured, which may affect the model training results. We do that by checking the total count of each label and presented in Table 1.

TABLE 1. Dataset Labels Ratio

News	Ratio (%)
Fake News	52.3
Real News	47.7

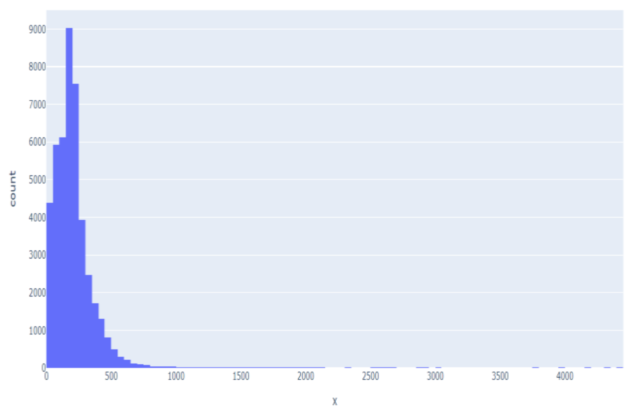

Fig. 4. Number of Words in the Text

Our proposed model was able to achieve an accuracy of 0.99% with the loss of 0.02%. We then conducted the classification report which is detailed in Table 2.

TABLE 2. Performance of NLP with LSTM

	Precision	Recall	F1 Score
0	1.00	0.99	1.00
1	1.00	1.00	1.00
micro avg	1.00	1.00	1.00
macro avg	1.00	1.00	1.00
weighted avg	1.00	1.00	1.00

TABLE 3. Compared with other Models

Models	Precision	Recall	F1 Score
SVM	0.68	0.86	0.76
Naïve Bayes	0.901	0.90	0.90
Random Forest	0.72	0.71	0.71
NLP with LSTM	**1.00**	**1.00**	**1.00**

Casting our minds back to the peak of the COVID-19 pandemic when the world was stuck indoors, we were left with nothing but digital life, sourcing information on the internet. This has led to challenges for the individual and the governmental level regarding whether what we consume as news is steadfast, factual or forged. Considering the fact that news articles are textual, therefore, we need to extract and analyze the text features. Henceforth, this study proposes the application of natural language processing (NLP) with long short-term memory (LSTM). In mining the text data, the techniques of NLP were used which enables us to renovate the unstructured text in the news article in the dataset into normalized, structured data suitable for analysis and model-driven algorithms.

Our experiment was able to achieve a good rate, though our interest is not for a higher rate, but to differentiate the real news from fake news. Clearly from the result, the conversion of unorganized context and text into an organized context and text with the help of NLP and LSTM are one of the core factors to streamline and manage fake news in real world. It is more perplexing to take out features from short texts to discover the concepts and content purposes of news (Samadi et al., 2021). Therefore, using NLP and LSMT to extract appropriate news is feasible (Chauhan & Palivela, 2021; Ibrishimova & Li, 2019).

VI. Conclusion

Fake news being misleading information presented to the audience as news has no future of ending since the revolution of technology has just begun. In view of this, more technological systems have been developed to control fakes news and its unforeseen damages. However, little is known about the application of combine natural language processing (NLP) with long short-term memory (LSTM) in fakes sieving. This study therefore employed natural language processing (NLP) with long short-term memory (LSTM) to detect fake news from real news. The experiment demonstrates that Natural Language Processing (NLP) and long short-term memory (LSTM) filtering accuracy is 0.99%, loss of 0.02% and an F1 score of 1.00%.

In future, we are looking at how best this model can be further transformed for real-time detection, for example, relationships between events and participants, as well as the credibility of sources and active respondents.

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