Fake News Detection Using Deep Learning and Natural Language Processing

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***Abstract*—The rise of social media has brought the rise of fake news and this fake news comes with negative consequences. With fake news being such a huge issue, efforts should be made to identify any forms of fake news however it is not so simple. Manually identifying fake news can be extremely subjective as determining the accuracy of the information in a story is complex and difficult to perform, even for experts. On the other hand, an automated solution would require a good understanding of NLP which is also complex and may have difficulties producing an accurate output. Therefore, the main problem focused on this project is the viability of developing a system that can effectively and accurately detect and identify fake news. Finding a solution would be a significant benefit to the media industry, particularly the social media industry as this is where a large proportion of fake news is published and spread. In order to find a solution to this problem, this project proposed the development of a fake news identification system using deep learning and natural language processing. The system was developed using a Word2vec model combined with a Long Short-Term Memory model in order to showcase the compatibility of the two models in a whole system. This system was trained and tested using two different dataset collections that each consisted of one real news dataset and one fake news dataset. Furthermore, three independent variables were chosen which were the number of training cycles, data diversity and vector size to analyze the relationship between these variables and the accuracy levels of the system. It was found that these three variables did have a significant effect on the accuracy of the system. From this, the system was then trained and tested with the optimal variables and was able to achieve the minimum expected accuracy level of 90%. The achieving of this accuracy levels confirms the compatibility of the LSTM and Word2vec model and their capability to be synergized into a single system that is able to identify fake news with a high level of accuracy.**

Keywords—fake news, deep Learning, natural language processing

I. Introduction

In today's world, information technology has given people various ways of consuming information, from social media to video streaming websites to audio podcasts. A wide range of information is at the tip of the fingers of people and sharable by them as well, further spreading the reach of this information. However, this has led to the rise of fake news because anyone can post information and this information may be unverified but to the general public may be assumed to be true. This spread of fake news can lead to many negative consequences. To solve this, it is proposed that an artificial intelligence that implements a deep learning algorithm coupled with Natural Language Processing (NLP) can identify whether information is genuine or fabricated with a high level of accuracy.

II. Problem Statememt

The rise of social media has brought the rise of fake news and this fake news comes with negative consequences. According to a study done to determine the trends in the spread of fake news, it was found that fake stories were 70% more likely to be retweeted on Twitter than true stories and took six times shorter to reach its target audience [1]. In addition, the main topic of these fake stories was determined with over 40 000 tweets from Twitter being related to politics.

Besides that, a study was done regarding false news related to COVID-19. From this study, a total of 1225 fake news stories were analyzed and it was found that half of the analyzed stories originated from social media. These stories spread misinformation such as false claims regarding the transmission of the disease, conspiracy theories linking the disease of political bodies and pseudoscientific and unproven treatments for the disease which could have severe health complications for those that believe in thestories [4]. With fake news being such a huge issue, efforts should be made to identify any forms of fake news however it is not so simple. Manually identifying fake news can be extremely subjective as determining the accuracy of the information in a story is complex and difficult to perform, even for experts. On the other hand, an automated solution would require a good understanding of NLP which is also complex and may have difficulties producing an accurate output [7]. Therefore, the main problem focused on this project is the viability of developing a system that can effectively and accurately detect and identify fake news.

III. Aims and Objectives

A. Aim

The aim of this paper is to study the effectiveness of a deep learning model combined with an NLP model in identifying fake news.

While an NLP model or deep learning model can perform fake news identification on its own, the overall accuracy of the

model is still far off optimal levels. It is proposed that a hybrid model of deep learning and NLP will provide a high level of accuracy when performing fake news identification.

B. Research Objectives

1) To design a fake news identification system using Long Short Term Memory (LSTM) (deep learning) and word2vec (NLP)

Both LSTM and word2vec have been used as a method of detecting fake news articles however this was done separately of each other. It is hypothesized that the integration of these two methods into a singular system would increase the effectiveness of performing the detection of fake news.

2) To determine the accuracy of the proposed system in identifying fake news

Most fake news detection systems used in today's world are still vulnerable to exploits and weaknesses in their system that can affect the accuracy when performing the detection activity. It is theorized that the proposed the system will correct these vulnerabilities and weaknesses in order to obtain a high accuracy level and low margin of error.

3) To identify any shortcomings of the proposed system Malicious parties will continuously attempt to circumvent these fake news detection systems by exploiting vulnerabilities and weaknesses for their own benefits. Therefore, it is essential to identify and correct any weaknesses in the proposed system in order to stay one step ahead of these parties.

IV. Technology and Scientific Theories and Methods

A. Long Short Term Memory

LSTM was chosen for this project because of its known suitability with natural language processing tasks. For example, LSTM models have the capability to remember long-term contexts which can be used to identify dialogue breakdowns. This is useful for conversational agents to detect such breakdowns in order for them to recover from mistakes. Another example is the classification of text into specific categories as demonstrated by Dabiri and Heaslip, where the use of LSTM and a convolutional neural network (CNN) yield results that indicated a superior level of performance compared to other algorithms. Furthermore, Liu et al. used an LSTM and CNN network to create a rumor identification classifier to be used in a social media environment. Results from the classifier showed that the models were capable of understanding hidden clues and contextual information [2]. These previous projects justify the decision to use LSTM for this project.

B. Word2vec

Word2vec was chosen for this project because it is capable of synergizing with an LSTM model, as shown from previous works. The clearest example would be a sentiment analysis conducted using Word2vec and LSTM for Indonesian hotel reviews. In that project, the Word2vec model was trained to assist the system learn the vector representation of words through the use of neural networks. The pre-processed review data was the input into the system while the output was the vector representation of every word. From the outcome of the project, an average accuracy level of 85.96% was obtained [3]. This showcases the compatibility of Word2vec together with LSTM.

V. Experiment Design

The proposed fake news detection system consists of two key components; the LSTM model and the Word2Vec model. The LSTM model consists of units that have several gates that maintain a hidden cell state that grants the ability to remember past information further than regular recurrent units [5]. The Word2Vec model, meanwhile, is a word vector representation method that can predict the word given a context window by carrying the semantic meanings of the word [6].

A cleaned and preprocessed dataset is inputted into a Word2Vec which will convert the text into vectors. Then, a tokenizer is used to classify the vectors. These vectors are then used to train the LSTM model by first being inputted into the embedding layer. The vectors are then passed through the LSTM layers until reaching the dense layer. Here, a sigmoid activation function transforms the input into a value of either 0 or 1 to signify fake or real news. The accuracy levels of both training and validation will be recorded.

VI. Results and Discussion

A. Independent and Dependent Variable Analysis

1) Training cycles

It was determined that the model was able to achieve a training accuracy of 1 as the number of epochs increased. However, the model trained using Dataset Collection 1 was able to achieve a validation accuracy close to 1 after 10 epochs but stagnated as the epoch increased. The validation accuracy of the model trained using Dataset Collection 2 also followed a similar trajectory with it achieving a validation accuracy range of 0.96 after 10 epochs with stagnation after as the epochs increased with even a slight decrease after 30 epochs.

Another issue that is apparent is the problem of overfitting as the number of epochs increased. This is proven when the validation loss begins to deviate from the training loss after 10 epochs, indicating that overfitting has begun to occur as a result of overtraining. The increase of validation loss also correlates with the plateauing of validation accuracy as the number of epochs increase.

2) Data diversity

TABLE I. Count of Subjects of Fake Dataset (Dataset Collection 1)

News	9050
Politics	6841
Left-news	4459
Government News	1470
US_News	783
Middle-east	778

TABLE II. Count of Subjects of True Dataset (Dataset Collection1)

politicsNews	11272
worldnews	10145

Figures 1 and 2 illustrate the subject of the news stories in Dataset Collection 1. With a focus on political news stories, the diversity of this dataset collection is lacking because of this focus. Moving on to Dataset Collection 2, the diversity of the data contained in these, while not being recorded in terms of subjects of every new story, comes from the various sources of the data, which are the users of the social media platforms the data was collected from.

3) Vector size

The increase in vector size does have a negative impact on the accuracy levels of the model with it decreasing. Given that the data count in Dataset Collection 1 is large, the effect of the increasing vector size on the accuracy levels in less significant with it more or less maintaining the same accuracy levels. This decrease is more clearly illustrated in Dataset Collection 2 where a vector size that was too large would weaken the training process as the lack of data would make it difficult to reach the target dimensionality. The accuracy score can have a decrease of up to 2.66%. This is further strengthened as Dataset Collection 1 had a data count of 44 897 while Dataset Collection 2 had a data count of 20 679 which is a 46% reduction of training data.

4) Fake news identification accuracy

TABLE III. CLASSIFICATION REPORT OF MODEL TESTED USING TEST SPLIT (DATASET COLLECTION 1)

	precision	recall	f1-score	support
0	1.00	1.00	1.00	5276
1	1.00	1.00	1.00	5949
accuracy			1.00	11225
macro avg	1.00	1.00	1.00	11225
weighted avg	1.00	1.00	1.00	11225

TABLE IV. CLASSIFICATION REPORT OF MODEL TESTED USING TEST SPLIT (DATASET COLLECTION 2)

	precision	recall	f1-score	support
0	0.98	0.97	0.97	2571
1	0.97	0.98	0.98	2599
accuracy			0.97	5170
macro avg	0.97	0.97	0.97	5170
weighted avg	0.97	0.97	0.97	5170

TABLE V. CLASSIFICATION REPORT OF MODEL TESTED USINGTEST DATASET (DATASET COLLECTION 1)

	precision	recall	f1-score	support
0	0.73	0.44	0.55	2656
1	0.59	0.83	0.69	2544
accuracy			0.63	5200
macro avg	0.66	0.64	0.62	5200
weighted avg	0.66	0.63	0.62	5200

TABLE VI. CLASSIFICATION REPORT OF MODEL TESTED USING TESTDATASET (DATASET COLLECTION 2)

	precision	recall	f1-score	support
0	0.97	0.91	0.94	2656
1	0.91	0.97	0.94	2544
accuracy			0.94	5200
macro avg	0.94	0.94	0.94	5200
weighted avg	0.94	0.94	0.94	5200

Figure 3 showcases the classification report of the fake news identification system after being tested with 25% of the training dataset of Dataset Collection 1. The scores of 1.00 across precision, recall and f1-score indicates a very high degree of accuracy. This is strengthened with an accuracy score of 99.76%. However, when tested with the Test Dataset, it was found that the system only achieved an accuracy score of 63.27%. Looking further into it, when referring to Figure 5, the precision score of 0.59 indicates that out of all the news stories the system predicted as fake, only 59% of them were actually fake. Furthermore, a recall score of 0.44 shows that out of all the true news stories, the system only correctly predicted 44% of them. This is a very poor performance from the system as it is below the target accuracy level of 90%.

Moving on to when the system was tested using the test split of Dataset Collection 2, precision, recall and f1-scores with the range of 0.97-0.98 led to an accuracy score of 97.49%. Furthermore, when tested using the Test Dataset, precision, recall and f1- scores of at least 0.91 culminated in an accuracy score of 94.02%, showing that the system is capable of identifying fake news as well as differentiating true news from fake news (Refer to Figures 4 and 6).

Given that Dataset Collection 1 had a focus on political news stories, when tested with a dataset that contained subjects other than politics, the system performed poorly as compared to when it was trained using Dataset Collection 2 which had more diversity in terms of subjects, giving the system more knowledge to make the correct prediction for new stories with different subjects.

B. Independent and Dependent Variable Analysis

TABLE VII. ACCEPTANCE OR REJECTION OF PROPOSED HYPOTHESES

Hypothesis	Description	Status
1	The number of epochs used during the training of the fake news identification system has a significant effect on the accuracy levels of the system.	Accepted
2	The higher the diversity of the training, the higher the accuracy levels of the fake news identification system.	Accepted
3	The vector size used by the word2vec model has a significant effect on the accuracy levelsof the system.	Accepted

Hypothesis 1 : This hypothesis is proven because that having the optimum number of epochs is key to achieving the maximum accuracy levels when training the fake news identification system. A low number of epochs would result in lower accuracy levels while too many epochs would lead to overfitting as a result of overtrainingthe model.

Hypothesis 2: This hypothesis is proven based on the results from the test dataset. When the system was trained using Dataset Collection 1, which has a lower diversity in terms of subject of the news stories as they were more focused on politics, resulted in achieved an accuracy level of 63.27% compared to when it was trained using Dataset Collection 2 that had more diversity because of the variety of sources that achieved an accuracy level of 94.02%.

Hypothesis 3: This hypothesis is proven in the results where as the vector size increased there was little to no changes of accuracy when the model was trained using Dataset Collection

1 but there was a significant decrease when the model was trained using Dataset Collection 2. These results show that there is a relationship between the vector size and the accuracy levels of the model.

VII. Project Contribution

The main contribution of this project is the creation of a fake news identification system that synergizes two methods; deep learning and NLP that is an improvement to existing fake news identification systems. This automated solution to the problem of spreading fake news provides a high level of efficiency and accuracy when performing its task. This will be extremely beneficial in the media industry, particularly social media, as it has been struggling to combat the spread of fake news across its media sources and platforms.

VIII. Conclusion and Recommendations

In conclusion, Objective 1 has been achieved as a fake news identification system has been developed with both those models. Objective 2 has also been achieved as the system is able to achieve an accuracy level of at least 90% which was the expected value with the only exception being when the

system was trained using Dataset Collection 1 and tested using the Test dataset. Objective 3 was achieved by analyzing the independent variables and determining a significant relationship between these variables and the accuracy of the system which means that selecting the incorrect variables will result in a poor accuracy level for the system. With these three objectives considered to be achieved, this project can be seen as a success.

The first recommendation for future projects would be to train the system with different datasets, preferably of a larger size than the ones currently used. Currently, the largest dataset used is the fake dataset in Dataset Collection with a data count of 23 502. This means that the diversity of the data used to train the system could still be increased significantly to further improve the accuracy of the system when it comes to testing it using separate datasets. However, even with a larger data count, the variety of content must also be taken into consideration as a dataset that has a large data count but narrow scope of subjects would still result in a poor accuracy level for the system as can be seen by the results of Dataset Collection 1 when tested with the Test dataset. The increase in data count would also require the optimal amount of training cycles and vector sizes to be found again to maximize the accuracy levels of the system. The second recommendation is to train the system with increased amounts of training cycles and vector sizes. This is to get a clearer picture on the significance of these variables towards the accuracy levels of the system as this increase would allow for the trends of the accuracy levels and loss levels to be more detailed in the resulting graphs. In order to do so within reasonable time constraints, the hardware used to train the system should have a more powerful CPU and RAM capacity to handles the larger epochs and vector sizes.

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