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Fake news detection for Arabic headlines-articles news data using deep learning

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ABSTRACT

Fake news has become increasingly prevalent in recent years. The evolution of social websites has spurred the expansion of fake news causing it to a mixture with truthful information. English fake news detection had the largest share of studies, unlike Arabic fake news detection, which is still very limited. Fake news phenomenon has changed people and social perspectives through revolts in several Arab countries. False news results in the distortion of reality ignite chaos and stir public judgments. This paper provides an Arabic fake news detection approach using different deep learning models including long short-term memory and convolutional neural network based on article-headline pairs to differentiate if a news headline is in fact related or unrelated to the parallel news article. In this paper, a dataset created about the war in Syria and related to the Middle East political issues is utilized. The whole data comprises 422 claims and 3,042 articles. The models yield promising results.

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1. INTRODUCTION

In the last decade, the widespread of the internet, communication, and mobile technology revolution have become noticeable. This revolution had a clear impact on the local and global transmission and exchange of information and news. Social media and online news websites started to boom and made it easy to get news for most people at any time and from anywhere in the world. The increased amount of time spent on social media sites is causing people to rely on these platforms for news to reduce or even dispense with traditional methods of accessing news and following up on information [1]. This development affects several positive aspects and negative aspects. The positives permitted a stable feeding of information, the free expression of opinion and bias to create an amiable conversation with minimal effort, speed of access and convenience. With social media and online websites, the world becomes much smaller. However, the reliability of this information considers a massive issue for the population. People always need to keep up to date with all life events occur around the world. The depending on social media for it, made the people believe all information and news which viral in tweets, links, or posts regardless of the credibility of sources and what is going on in front of them. All of this leads to the creation of fake news.

The concept of fake news is not new. It has existed before the broad spreading of the internet as users publish bogus data could be a thrill, incomplete or partial to confound the users and block their capacities to separate what is valid from what is not to accomplish financial or political purposes. In addition, today's fake news maybe includes tampered photographs and videos, which increase the suspicion of individuals.

With the rapidly spread of social networks, the danger of disastrous effects of the fast spread of bogus news over the online social networks (OSNs) is detonating. In the same situation, counterfeit news consistently leads to stir up struggle and issues. Over the most recent years, the spreading of phony news that published on the internet has increased and has accomplished the purpose of affecting social and political substances. As an example, this study [2] showed the critical effect of fake news regarding the 2016 US presidential elections. Publishing fake news is a global issue and should be considered as a crime with very severe punishments. Therefore, we cannot simply trust social media platforms to be a reliable and neutral source of information in general and news in specific. We should verify the sources. On the other side, the advancement of the Internet and technology alert the researchers to exploit the technology development in machine learning and artificial intelligence in their research and studies to find a system to predict and distinguish false news [3].

Fake news issue is not an easy issue to handle it. Researchers tried to provide a way to manage internet news and inform social media users whether what they are posting is fake or real. There are many proposed models to detect fake news using machine-learning algorithms to detect all fake news types. The main issue with these systems is that most of them they used English dataset. The existence of machine learning models that support the Arabic language is still very limited. This research focuses on the Arabic fake news detection issue and proposes different deep learning models to support this matter.

The following section presents a brief background of news carrier types and the different data types that news' carriers provide as output. Section 3 explains some related work to detect fake news in both languages: English and Arabic. In section 4, we propose our methodology that we adopted to define our models. Our results are discussed in section 5. Finally, the conclusion of the paper is displayed in section 6.

2. OVERVIEW AND BACKGROUND

News carriers have various kinds of media outlet that publish news topics and stories. The massive amount of news information that flowing through these carriers is heavily depends on the public population due to the need of this knowledge worldwide. The dependence on information posted on social media has increased as more people begin to feel more convenient with their social media accounts. In the United States of America, 6 out of 10 people get news from social media [4]. Another study in 2017 [5] appeared that around 67 percent of American grown-ups are depending on the OSNs, e.g., Twitter Inc., Facebook Inc. and Snapchat for news, contrasted with 62 percent in 2016. This section shows diverse data types for news carrier platforms to institute a basis for how to create and implement fake news.

2.1. Types of news carrier platforms

News carrier platforms are divided into two platforms: standalone websites and social media.

a. Standalone website: a standalone website consists of any type of website that produces news, and there are three main types of these websites: i) popular news sites: their presence on the internet is vast, and they usually have a social media position with a large number of followers [6], ii) blog sites: these sites are smaller than popular news sites and contain user-generated content. Its content is usually given from a personal perspective. This type of sites is a high-risk area for information since it comes directly from a user's bias rather than finding credibility in facts on a specific topic [6], and iii) media sites: these sites are not the same as social media. Media sites focus more on providing different media content from photography, news, videos, and tutorials.
b. Social media: the easiest form of news travel is the sharing of information among people on social media. In 2017, 78% of users under-aged 50 years stated that they publish news on social websites including Twitter and Facebook [5]. This statistic displays the nature of social media and the spreading false information behavior.

2.2. Types of news data

Comprehension the types of various data platforms is important to understand the ways of getting the information from the internet. There are four main categories of data types: i) text: a part of semantics that spotlights the text as the type of correspondence. It does have punctuation and grammar to promote voice and tone [6]; ii) audio: audio is a sound. It does not show any type of visual to the user so, it acts differently from other media forms; iii) hyperlink: it is a way to link the user between two connected pages. Usually, a hyperlink is connected to a host website from ads, and in fake news is often the source of how 'clickbait' transactions work; and iv) multimedia: multimedia means the collection of video, graphics, and audios.

3. LITERATURE REVIEW

Recent related works examined the widespread of fake news across social websites and proposed models to detect fake news, which can be defined as the forecasting of the ways of news articles to be designedly swindling [4]. English fake news detection had the largest share of studies, unlike Arabic fake news detection, which is still very limited. In this section, we show some of these researches on both Arabic and English datasets.

Figueira and Oliveira [3] presented two possible methods to detect fake news, which is totally opposite using algorithms and human involvement. The first one is based on the users to flag the fake news by fact-checkers from media communities such as Snopes.com. In addition, the second one is to use models and algorithms to check the validity of the information origins and determine fake content. In their views, this approach does not gain significant solidity to identify which information is false or not, properly. The authors proposed that the source must be tracked and assigned a score value due to periodic assessments done by a trustful third-party system. The authors concluded that it is potential to recognize objective elements -the facts- in social media websites posts, which can help in fighting fake news in addition to the algorithms such as: machine learning, text mining, and the necessary hardware to access big data for training the algorithms.

Borges *et al.* [7] developed a deep learning model to address the stance detection challenge, influencing max pooling together with bidirectional recurrent neural networks (RNNs) and neural techniques to build representations from the body and from the headlines of news articles and consolidating these representations with external correspondence features. Mahir *et al.* [8] proposed an approach to analyzing fake news messages from social media posts, by finding how to expect accuracy assessment. Afterward, they compared five algorithms of machine learning to explain the efficiency of the classification execution on the dataset. The experimental result showed that naïve Bayes and support vector machine (SVM) classifier outperforms the other algorithms. Nair *et al.* [9] presented some of the content types for fake news and algorithms used to detect and identify them. The major problem of fake news detection research is the lack of existence of fake news data set in different fields. This will affect the performance of the model. Therefore, this paper found a general algorithm to detect fake news.

Ahmed *et al.* [10] presented a model for detecting fake news using n-gram analyses and six different supervised classifications. For comparison between techniques, they used term frequency (TF) and term frequency-inverted document frequency (TF-IDF) as feature extraction with different sizes of the n-gram from unigram to four-gram. In their study, they compared six various supervised machine learning techniques. They collected a new dataset from real sources and concentrated on the political news sector. They collected real news articles from Reuters.com and Kaggle.com fake news datasets. They also tested their algorithm on generally available datasets Horne and Adali [11]. Upon their results, the experimental evaluations showed that the Lagrangian SVM classifier and TF-IDF feature extraction achieved the highest accuracy of 92%. Qawasmeh *et al.* [12] using different deep learning models to detect fake news, they applied their models on the FNC-1 dataset, which is a headline-article English dataset. The proposed model is a bidirectional long short term memory (LSTM) concatenated model and multi-head LSTM model, with accuracy 85.3% and 82.9% respectively.

Vedova *et al.* [13] proposed a machine-learning model to detect fake news. This model combines social context and news content features depending on social interactions like several shares of Twitter. The authors claimed that their algorithm outperforms other existing algorithms by 4.8%. In addition, they integrated their method to the chatbot of Facebook Messenger and obtained an accuracy of 81.7% by checking the validity of it with a real application.

Since identifying the rumors at the publishing time is a very important aspect, Alkhair *et al.* [14] have proposed a novel scheme that collects, analyses, and classifies Arabic fake news from YouTube. To collect their data, they used YouTube API, which retrieves all the videos with some certain criteria. They used three different classifiers to distinguish between the rumor's comments and the non-rumors. They found that the result depends on multiple features as the rumor topic and the used classifier. Rangel *et al.* [15] is trying to recognize the misleading messages that were written to seem authentic while not in Twitter messages and news headlines. The collected data sets were created in [16].

The prevalence of fake news is a social case that is widespread at the social level through social media websites such as Facebook and Twitter and between people. Fake news that we are attentive in is one of many types of fraud in social websites, but it is a more important one as it is created with unfair intention to delude people [17]. Girgis *et al.* [17] construct a model that can forecast if some news is fake or not based only on its content, that way oncoming the problem from a deep learning view by RNN technique models including LSTMs, vanilla, and GRU. Kaur *et al.* [18] proposed a novel multi-layered voting ensemble model. The model tested using twelve classifiers on three datasets.

Bauskar *et al.* [19] construct a machine learning approach depends on natural language processing (NLP) techniques for fake news' detection by using both social features of news and content-based features. The proposed model achieved F1 score of 90.33% with an average accuracy of 90.62%. In study [20], a new fake news detection model was presented, called fake news detection model using grammatical transformation on deep neural network. Aldwin and Alwahedi [21] proposed an efficient approach to permit users to install a tool into their personal devices and use it to detect possible click baits. The major results performed to evaluate the method's ability to achieve its desired goal showed high performance in recognizing potential sources of fake news. In study [22], Torabi and Taboada were conducted a modeling trial to demonstrate the sources and gaps of imbalanced datasets for future guidance. In 2020, Ozbay and Alata [23] applied twenty-three artificial intelligence models to discover fake news using the Document-Term Matrix and TF weighting method.

4. METHOD

4.1. Overview of dataset

The aim of this study is to discuss the Arabic fake-news issue, recognize untrusted news and enhance the detection tools. The news headline plays a major role in the reader's attention and completes reading the news or not. Therefore, the dataset consists of a claim headline and article-bodyline. The dataset is created by a group of researchers in 2018 [24] and can be downloaded from [25]. The data was created about the war in Syria and related to the Middle East political issues. The whole data comprises 422 claims and 3,042 articles. Each claim can match different articles, and other features including ID, fact, URL, stance. The source data is provided as 422 JavaScript File. Table 1 illustrates the source data format with all the feature's description [25]. The dataset stances labels were for each claim- article pair from fake news challenge (FNC) dataset [26], [27]. Table 2 illustrates the description of each stance.

Table 1. The dataset features description

Feature	Description
ID	The claim ID
Claim	The claim textual content
Fact	The factuality label of the claim (true or false)
Article	The list of articles we retrieved for each claim using the Google Search API
URL	The Links to each article
Stance	The stance of each article to the claim (agree, disagree, discuss or unrelated)
Rationale	Line's location in each article that contain the rationale for agreement or disagreement with the claim

Table 2. The Dataset stances' description

Label	Description
Agree	The article concurred with claim
Disagree	The article not concurred with claim
Discuss	The article and claim discussed the same idea. However, it is not congruent with each other
Unrelated	The article and claim discussed different idea

4.2. Data preprocessing

The source dataset is provided as JavaScript files. The dataset was converted to .csv format, which results 3,042 records. Table 3 shows a set of data records examples. Then, we apply some preprocessing to be ready for deep-learning models. Figure 1 illustrates the preprocessing steps of the dataset.

4.2.1. Data cleaning

First, we check all empty values and remove the records, which have any empty cell. After removing it, we got 3,037 records. In our study, we focused on headline article data. Therefore, we ignore all other features like ID, fact, and URL. Finally, we work on the headline-article dataset in .csv format, which comprises 3,037 records with three features including claim, article, and label. In addition, we remove all non-Arabic characters and numbers, punctuation, and stop-words. Our dataset is split into three sets: training, validation, and testing. The ratio of these sets is 60%, 20%, and 20% respectively. The testing dataset was isolated before the training step and it is only utilized for the model valuation.

4.2.2. Feature extraction

Because the neural networks do not accept a text as-is. Re-representing all texts into numerical form is a mandatory step. Table 4 illustrates a simple description of all of them. In our research, we choose a Word2Vec approach [27] with a previous training model called the Gensim model.

Table 3. Stance labels description

Claim	Article	Label
" قال مصدر مطلع يوم الأربعاء إن فصائل كردية ألقت القبض على متشددين إسلاميين فرنسيين مشتبه بهم في شمال سوريا بينهم رجل أدين في السابق بإدارة شبكة لتجنيد الجهاديين في فرنسا" An informed source said on Wednesday that Kurdish factions had arrested suspected French Islamist militants in northern Syria, including a man previously convicted of running a jihadist recruitment network in France.	"فصيل كردي سوري يحتجز متشددين فرنسيين مشتبه بهم في سوريا - مورينيوز - وكالة إخبارية موريتانية مستقلة الأحد، يناير 21 , 2018 فصيل كردي سوري يحتجز متشددين فرنسيين مشتبه بهم في سوريا باريس (رويترز) " Syrian Kurdish faction detains suspected French militants in Syria - Mourinhos - Independent Mauritanian news agency Sunday, January 21, 2018 Syrian Kurdish faction detains suspected French militants in Syria Paris (Reuters)	agree
" قال مسؤولون من المعارضة السورية إن مقاتلي المعارضة في جيب تتقاطع عنده الحدود السورية واللبنانية والإسرائيلية يتفاوضون على صفقة مع الحكومة للرحيل إلى مناطق أخرى تحت سيطرة المعارضة" Syrian opposition officials said rebels in an enclave where the Syrian, Lebanese and Israeli borders intersect are negotiating a deal with the government to move to other rebel-held areas.	"فصيل كردي سوري يحتجز متشددين فرنسيين مشتبه بهم في سوريا - مورينيوز - وكالة إخبارية موريتانية مستقلة الأحد، يناير 21 , 2018 فصيل كردي سوري يحتجز متشددين فرنسيين مشتبه بهم في سوريا باريس (رويترز)" Syrian Kurdish faction detains suspected French militants in Syria - Mourinhos - Independent Mauritanian news agency Sunday, January 21, 2018 Syrian Kurdish faction detains suspected French militants in Syria Paris (Reuters)	unrelated

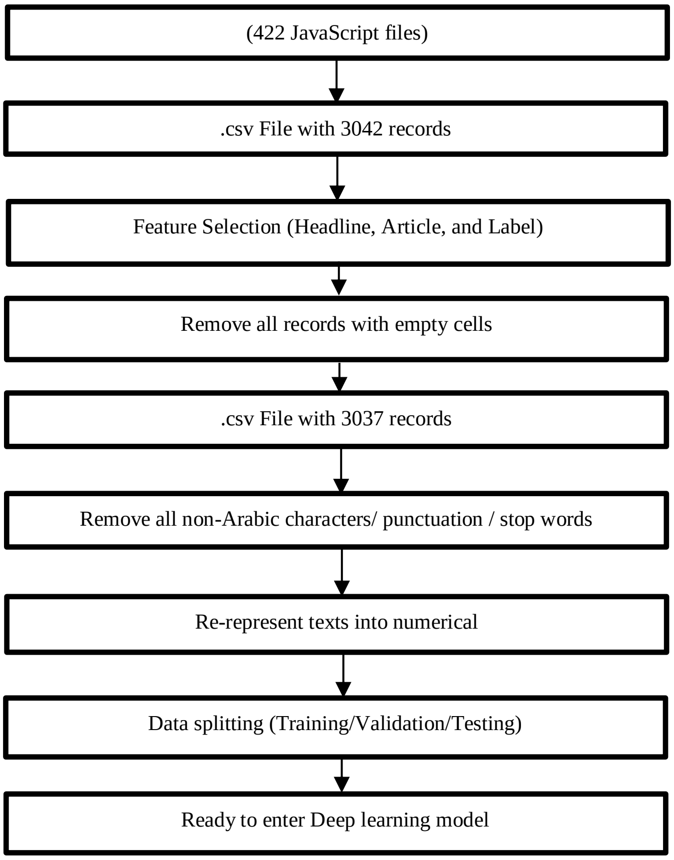


Figure 1. Dataset preprocessing steps

Table 4. Word embedding details

Word Embedding Approach	Each word is converted to a sequence of numbers; these numbers were considered as beginning weights.
Word-2-vec Approach	This approach is better than the previous one in terms of the total training model time. It is capable to utilize any already trained model as Gensim model. So, the weights enhancement occurs before the training model [27].
Genism pre-trained model	This model is utilized for pre-training on the same utilized dataset. When we applied it to our dataset, which included 3037 records, we got 158910 unique words.

4.3. Model architectures

After running many experiments, we proposed two models including model 1 Arabic fake news headline-articles long short term memory (AFND-LSTM) and model 2 Arabic fake news headline-articles convolutional neural network long short term memory (AFND-CNN-LSTM). In this section, we will illustrate both models in detail.

Figure 2 provides model 1 (AFND-LSTM) and model 2 (AFND-CNN-LSTM). Both models are shown in Figures 2(a) and 2(b), respectively. In both models, before entering the claims and articles over the input layer, the merging step is applied to them. After that, the embedding layer is performed. As we mentioned above, the Gensim training model is utilized in our models. In model 1, the embedding layer result passed through LSTM hidden layers [28] with memory unit: 150 and dropout: 2, then we normalize the values which resulted from the hidden layers using batch normalization [29]. The output is passed through three dense layers, separated by one dropout layer (256, 128, 4 units) respectively. But in model 2, the embedding layer result is entered over two convolution neural network hidden layers (32 and 64 filters). In order to evade over-fitting in the model, the max-polling layer [30] should be applied after each convolution neural network hidden layer. After that, the result is entered over the LSTM hidden layer [28] with memory unit: 150 and layer_number: 5 followed by the flattening layer, which is mandatory. The next step was to feed the result over one dense layer (4 units). Finally, in both models, the last layer is performed using the soft-max activation function to yield labels classification. For the training process, our loss function is: "was sparse categorical cross-entropy" [31] and the optimizer is "Adam" [32].

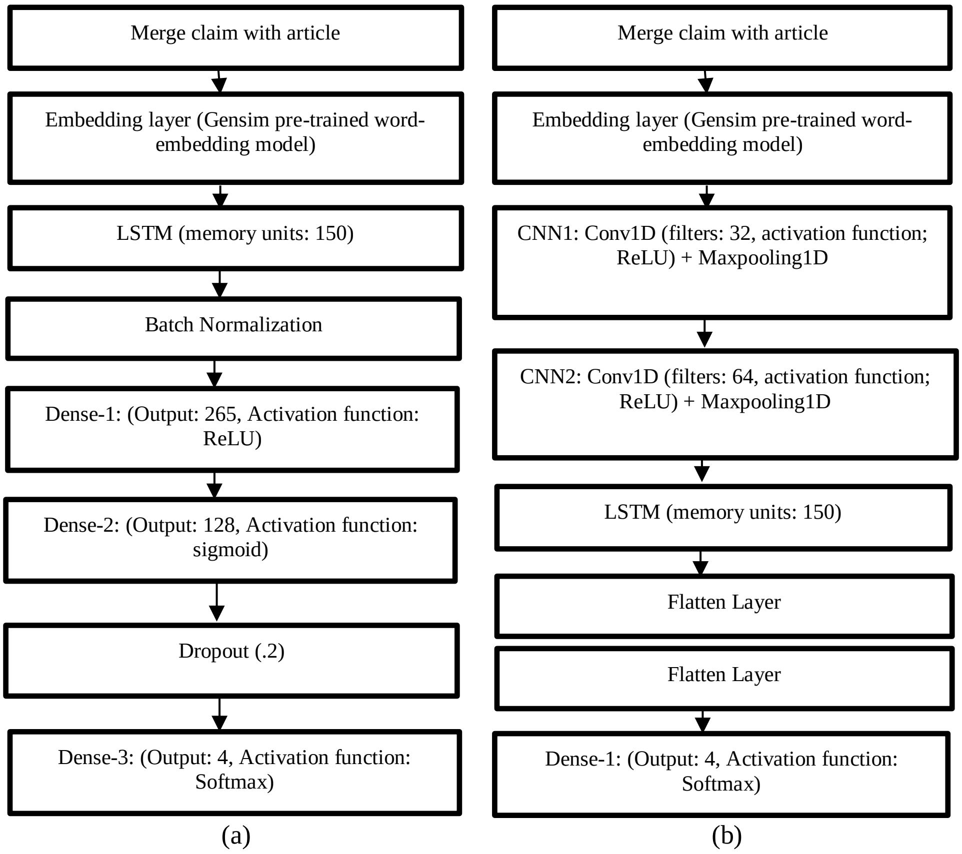


Figure 2. Arabic fake news detection models (a) model 1 AFND-LSTM and (b) model 2 AFND-CNN-LSTM

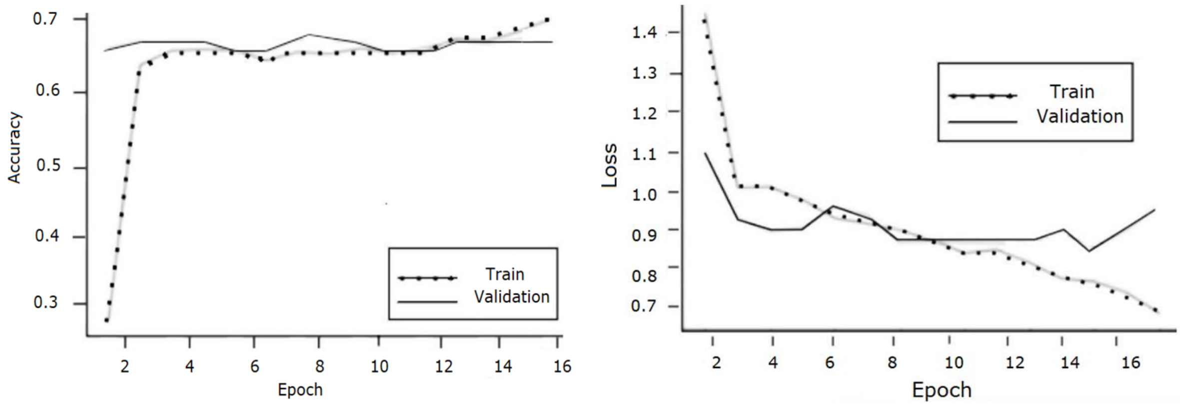
5. RESULTS

The online python platform Google Colab [33] was utilized. Different hyper-parameters are included in our models, such as word embedding models, embedding dimension, loss, and optimizer functions. The values found in the models rely on our experiments.

Many experiments were conducted; we proposed two models to distinguish Arabic fake news headline-articles issue. As we mentioned before, model 1 AFND-LSTM and model 2 AFND-CNN-LSTM. Model 2 yields a better accuracy. Table 5 shows a set of evaluation for both models. Figure 3 provides model accuracy and model loss. Figures 3(a) and 3(b) show accuracy and the loss function for training and validation sets over time for model 2.

Table 5. Evaluation statistics

Model	Accuracy	Precision	Recall	F1-Score
Model-1: AFND-LSTM	68.2 %	0.7	0.0	0.0
Model-2: AFND-CNN-LSTM	70 %	0.6	1.0	0.75



(a) (b)

Figure 3. Model 2 accuracy and loss function during training (a) accuracy and (b) loss

6. CONCLUSION

Fake news has the objective to become widely among people. With the existence of social media platforms like Twitter and Facebook, it becomes easier for false information to widespread quickly. The fast accessibility and publicity are being misapplied by many people to disseminate fake news. Creating results in a negative influence on people and society. This paper presented a deep learning method to address Arabic stance detection problems to address the Arabic fake-news issue, improve automatic detection tools and recognize unreliable news. A specific dataset is used to support this idea. Therefore, it consists of claim headline and article bodyline. Then, we apply some pre-processing such as data cleaning and features extraction to be ready for deep-learning models through analysis of word embedding in which the main phase involves cleaning the data and splitting dataset into 60%, 20%, 20% for training, validation, and testing, respectively.

The obtained results show that AFND-CNN-LSTM gives better accuracy than AFND-LSTM; it resulted in 70% accuracy in comparison with the first model that results in 68.2%. Which means that when we combine two models together, the result is improved in accuracy, precision, and recall. Despite the promised results, there are also potential thoughts for future work. One of the future works includes improving the accuracy for models by adding more layers or by combining the models with other classifiers. This paper has written with the prospect that this model helps in improving the detection of false news and makes readers conscious of misinformation, so they are less liable to spreading lies.

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