Iraqi Journal for Computer Science and Mathematics

Journal Homepage: http://journal.esj.edu.iq/index.php/IJCM
e-ISSN: 2788-7421 p-ISSN: 2958-0544

Approach for Detecting Arabic Fake News using Deep Learning

Khalid Shaker * Arwa Alqudsi

College of Computer Sciences and Information Technology,
University of Anbar, Ramadi, Iraq

*Corresponding Author

DOI: https://doi.org/10.52866/ijcsm.0000.00.00.000
Received 00 Month 2000; Accepted 01 Month 2000; Available online 02 Month 2000

ABSTRACT: Fake news has spread more widely over the past few years. The development of social media and internet websites has fueled the spread of fake news, causing it to mix with accurate information. The majority of studies on Fake News Detection FND were in English, but recent attention has been focused on Arabic. However, there aren't many studies on Arabic fake news detection. In this work, a new Arabic fake news detection approach has been proposed using Arabic dataset publically available and a translated English fake news dataset into Arabic. A new model Text-CNNs based on 1D Convolution Neural Networks CNNs has been used for classification real and fake news. Extensive experimental results on the Arabic fake news dataset show that our proposed approach provided high detection accuracy about (99.67%), Precision (99.45), Recall (99.65) and F1-score (99.50).

Keywords: Fake news; FND; Deep learning; CNNs

1. INTRODUCTION

The increased use of social media and chat messaging services in recent years has altered not just how people interact but also how they get news items and how much faith they have in its content. According to estimates, 66% of people in the Middle East regularly check for news on social media [1]. Young adults view social media as a crucial source of news and information. Users have increasingly turned to popular chat messaging services like WhatsApp, Facebook Messenger, Snap Chat, and LINE to curate their own news consumption. Users only see the hand-picked news stories they have chosen to view [2].

Fake news detection (FND) is defined as “the prediction of the chances of a particular news article (news report, editorial, expose, etc.) being intentionally deceptive” [2]. There is a lot of interest in FND tasks among NLP researchers. The research community has recently become interested in using machine learning, and specifically deep learning-based methods, to uncover these occurrences [3]. The majority of fake news detection research relies on machine learning methods. These methods are feature-based since they call for the identification and selection of features that can be used to determine whether a piece of information or text is phony. The chosen machine learning model is then given these features in order to perform classification [4].

Deep learning models have lately demonstrated effectiveness in text classification and fake news identification across a variety of languages. They benefit from the ability to automatically change internal settings until they determine the appropriate characteristics to distinguish between various labels on their own [5, 6]. Convolutional Neural Networks (CNNs), a subclass of deep learning, outperform in computer vision issues due to their capacity for convolutional operation, which extracts features from local input patches and promotes modularity and data efficiency in representations. CNN is the greatest option for computer vision-related tasks because to a number of characteristics that also makes them a key component of sequence processing, including classification of texts. Because every patch receives the same input transformation, 1D convolution layers are also translation invariant in the sense that a pattern acquired at one point in a phrase may be recognized at another. As with 2D CNNs, 1D patches may be taken from an input and used to output the maximum or average value, a process known technically as Max Pooling or Average Pooling, respectively. As with 2D CNNs, this is also used to shorten the 1D input.

A lot of studies and datasets have already been published in the field of detecting fake news in English. Fake news detection in Arabic is still in its infancy and needs a lot of improvement before it reaches the level attained in other languages, particularly English. Therefore, a system that automatically aids in checking the veracity of disseminated information is needed to combat fake news [7]. There aren't many publications that discuss how to spot fake news in Arabic-language forums. The reason for this is that one of the most difficult areas in natural language processing is

**Corresponding author: khalidalhity@gmail.com*

Arabic. First, the way that words are formed and spelled might change from one phrase to the next, drastically altering the meaning of the term. Additionally, there are several dialects of the Arabic language, some of which are wholly distinct from others [8].

1.1 RESEARCH OBJECTIVES

In this work, significant contributions have been done to the realm of knowledge. The main goals of this work are as follow:

- Dataset Development: This investigation will translate an English fake news dataset into Arabic since there are few resources for detecting Arabic fake news. Besides, it will use another set containing real and fake news collected from Arabic Facebook pages. Such an endeavor will be instrumental in creating a strong model which employs various training materials mirroring actual situations.

- Creating models: The aim here is to come up with an original deep-learning architecture using Convolutional Neural Networks (CNNs) to create Text-CNN model that can classify different kinds of Arabic news as either ‘real’ or ‘fake’. In processing language, the 1D CNN-based model takes advantage of strengths associated with dealing with sequential data such as text.

- Comparing methods: In order to check whether the suggested Text-CNN performs better than other techniques used before on detecting fake news in Arabic language; comparisons shall be done with previous related works.

The remainder of this paper is organized as follows. Section 2 provides approaches that were based on earlier researches. Sect. 3 covers the overall strategy for solving the problem and the methods used. The effectiveness and assessment of our approach are discussed in Section 4. Sect. 5 concludes the study and defining the area of additional future research

2. RELATED WORK

Due to its many subjects and problems, Natural Language Processing (NLP) for the Arabic language has emerged as a particularly fascinating and challenging study area. Using seven English datasets and translating two of them into Arabic, a ClaimRank model for identifying check-worthy claims was created in [9]. Following that, features were retrieved utilizing methods including TF-IDF, part-of-speech tags, emotion scores, weighted bag of words and sentence length (in tokens). Authors included a language detector for Arabic adaption, and after that they trained their model using a Neural Network (NN) with two hidden layers. Using machine learning and deep learning approaches, the authors of [10] created a strategy with many steps for identifying fake news about COVID-19 on social media. They first created a sizable Arabic dataset associated with COVID-19 and utilized pre-processing techniques to clean the data and eliminate unnecessary components. TFIDF and word embedding were then used as two feature-extraction approaches to extract the features from the data. The SVM classifier had the greatest accuracy (87.8%) after they employed several machine and deep learning classifiers.

Alkhair, et al.'s recent study [11] used YouTube responses and comments to evaluate misleading information material in the Middle East, including data collected via postings on the YouTube app. Three things best describe Alkhair and his team's contribution: They created a new Arab corpus for fake news research and analysis by first gathering 4079 comments from three chosen prominent Arab celebrities using the YouTube API, and then cleaning the data by removing special characters, words in foreign languages, URL links, and repeated comments. Second, they gave researchers a range of analyses on the data they should seek for in order to learn more about the topic of false news identification. Alkhair, et al. tested the likelihood that YouTube comment rumors and facts were true using three machine learning classifiers: Multinomial Nave Bayes (MNB), Support Vector Machine (SVM), and Decision Tree (DT). In the end, they were able to get a 95.35% accuracy rate by employing the SVM classifier. Recently, the authors in [12, 24] used the AraNews dataset to construct their models. This study used the Term Frequency-Inverse Document Frequency (TF-IDF) approach to extract word vectors or features. Next, bogus news was predicted using Random Forest Classifier, Naive Bayes, and Logistic Regression. The Random Forest Classifier has the highest accuracy (0.866), while the accuracy of the other two models is (0.844 and 0.859), respectively.

By proposing a technique for autonomously creating possibly fake Arabic news items, [13, 23, 25] addressed the problem of not having enough relevant data to train detection algorithms. Additionally, they developed models to recognize Arabic news that has been modified which led to the successful discovery of fake Arabic news. They tested their model using their newly created AraNews datasets. The dataset contains 3,072 true sentences and 1,475 false sentences. F our pre-trained masked language models (MLM): mBERT, AraBERT, XLM-RBase, and XLM-RLarge have been used, with the AraBERT model achieving the highest accuracy rate of 89.23%. A further illustration is the comparison made by Harrag et al. [14], who offered a content-based approach based on CNN to solve the problem of fact-checking. The task of fact-checking comprises determining if a textual claim's facts are true or false. The Arabic Fact-Checking and Stance Detection Corpus was used in this work. The suggested model was trained using a variety of carefully selected characteristics. The effectiveness of the fact-checking assignment in spotting Arabic fake news was demonstrated through investigation with a 91% accuracy rate. Alyoubi et al. [15] proposed a DL-based method for spotting false information on Twitter. The proposed method takes use of the news content and social context of the news dissemination participant. They examined the efficacy of the Keras embedding layer using well-known pre-trained word embeddings (word2vec, fastText, ARBERT, and MARBERT) in order to find a good model for the false news detection challenge. The contextual embeddings ARBERT and MARBERT produced the greatest word representations, and these embeddings also showed the best model performance. Regarding DL methods, the CNN-based model architecture fared better than the BiLSTM in the majority of the scenarios. The highest-performing model with great accuracy and an F1-score of 95.60% was produced by combining MARBERT and CNN. Moreover, Awajan et al. [16] have built an intelligent classification system to identify fake news in Arabic-language tweets. In this work, they have compared deep learning with shallow learning. A newly created dataset of tweets obtained from the Twitter API was created in order to test both shallow and deep classifiers. After the models were run on the dataset, the pre-trained BERT model produced an accuracy rating of 99%, outperforming all other classifiers. The other models' accuracy was 96.71% for LSTM and 95.92% for shallow learning.

3. THE PROPOSED APPROACH

The block diagram of the proposed model is shown in Figure 1. The objective of this work is to increase the efficacy of the suggested Arabic fake news detection model. This section explains the suggested methods that used to identify fake news in Arabic, starting with outline the datasets that have been used, the pre-processing procedures, and finally the architecture of the suggested Text-CNN model.

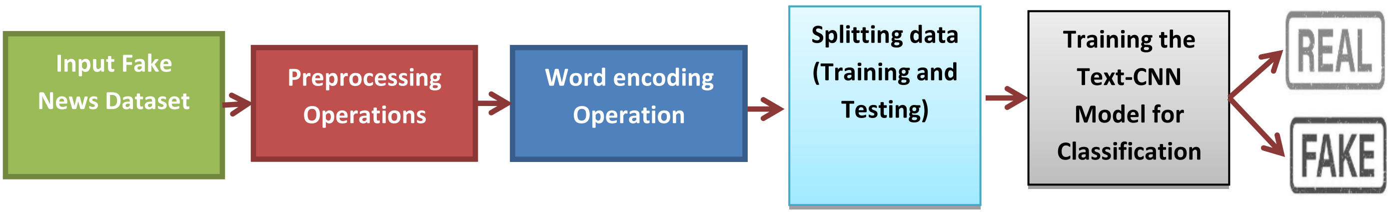

FIGURE 1. - The block diagram of the proposed Arabic fake news detection model

3.1 DATASET

In this work, two datasets have been used for Arabic fake news detection task. The first one is English translated dataset that collected by Information Security and Object Technology [17], the dataset includes two different kinds of articles: fake news and real news. The real items were got by crawling the Reuter's news website, whereas the false news stories were gathered from dubious websites. This dataset was compiled from actual sources. The collection includes a variety of articles on a range of subjects, however the majority of the articles are on political and global news issues. The dataset consists of two CSV files labeled true and fake, 5000 fake and genuine news items have been utilized from this dataset. The second dataset [18], consist of two categories: 1000 real news collected from the Facebook pages of reliable Arab news channels such as Al-Arabiya, Al-Jazeera, Al-Hurrah Iraq, etc., and 1000 fake news from the famous Iraqi anti-rumors page (the technical for peace). The distribution for real and fake news of both datasets has been showed in Figure 2. Table 1 shows a samples of real and fake news in the datasets.

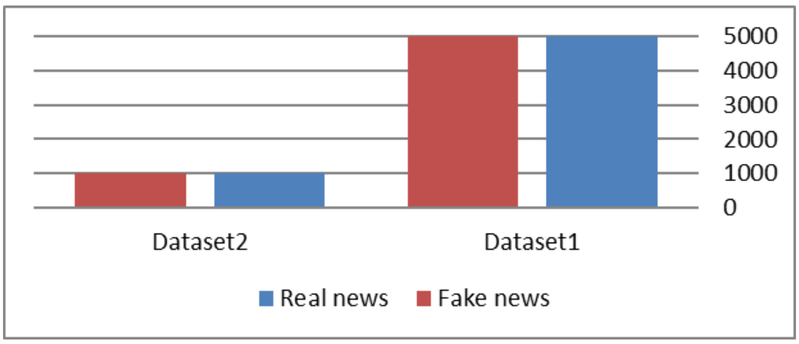

FIGURE 2. - The distribution for real and fake news

Table 1. – Sample of news in the dataset

REAL	FAKE
إدارة نادي الميناء، تتم إجراءات انتقال مهاجم جديد الى صفوف فريقها، قادما من الزوراء، لتمثيل "سفانة الجنوب" في مرحلة الإياب من الدوري العراقي الممتاز لكرة القدم.	افتتح قبل قليل في بغداد الفرع الثاني لوكالة ستاربكس في الجادرية مقابل جامعة بغداد بحضور نخبة من مشاهير الرياضة والفن
العاملون في القطاع الاجتماعي والطبي يجريون إضرابا وطنيا في باريس يدعو إلى تحسين ظروف العمل والدعم في أماكن عملهم.	اعتقال بابا نويل في بغداد بسبب سرقته قناني غاز من بيوت عدد من المواطنين

3.2 THE PREPROCESSING STAGE

Text pre-processing focusses on converting the raw data into a well-defined structure where the words that do not contribute into the contextual meaning of the sentence are discarded. Being an important part of natural language processing, text pre-processing can be done in various ways as there are various techniques available for the same. The choice of technique can be as per the demand of the problem but there are a few techniques that must be used with every problem to enhance the performance of the models. The techniques need to be applied in a specific order to provide the best results possible.

The process of getting the text ready for classification in fake news detection is known as data pre-processing. The pre-processing procedures used in this study include tokenization, punctuation removal, and stop word removal. Tokenization is a vital step in the process of dividing a text into meaningful chunks, or tokens. If a token is represented as a stop word or a punctuation mark, consider removing it.

3.2.1 Tokenization

In this step primarily breaks up or splits the sentence into an array of words which are referred to as tokens. The sentence is usually split up on space between two words or even when punctuation is encountered depending on what condition might be applied. Table 2 has an example of tokenization process.

Table 2. - Tokenization example

Raw news	After tokenization
% رصد نسخة من #كورونا تعد *مزيجاً* من متحوري دلتا و أوميكرون !	"%", "رصد", "نسخة", "من", "#", "كورونا", "تعد", "*", "مزيجا", "*", "من", "متحوري", "دلتا", "و", "أوميكرون", "!"
% Monitoring a version of #Corona that is a *mix* of the Delta and Omicron mutants!	"%", "Monitoring", "a", "version", "of", "#", "Corona", "that", "is", "a", "*", "mix", "*", "of", "the", "Delta", "and", "Omicron", "mutants", "!"

3.2.2 REMOVAL OF PUNCTUATIONS

Raw data has lots of instances of punctuations or special characters (@, $, *,) which are not of much importance nor is understood by the machine. Therefore its existence in data just contributes to the noise in it and should be removed. For same example in tokenization the sentence will appear in Table 3 after tokenization and removal of punctuations.

Table 3. - Raw news after tokenization and removal of punctuations

Before removal of punctuations	After removal of punctuations
"%", "رصد", "نسخة", "من", "#", "كورونا", "تعد", "*", "مزيجا", "*", "من", "متحوري", "دلتا", "و", "أوميكرون", "!"	"رصد", "نسخة", "من", "كورونا", "تعد", "مزيجا", "من", "متحوري", "دلتا", "و", "أوميكرون"
"%", "Monitoring", "a", "version", "of", "#", "Corona", "that", "is", "a", "*", "mix", "*", "of", "the", "Delta", "and", "Omicron", "mutants", "!"	"Monitoring", "a", "version", "of", "Corona", "that", "is", "a", "mix", "of", "the", "Delta", "and", "Omicron", "mutants"

3.2.3 REMOVING STOP WORDS

NLP is extracting keywords about a particular topic depending on the use case. Hence for Arabic text classification or other problems, pronouns and prepositions such as ("من ", who), ("في ", in), or ("على ", on) etc. are not of importance and are quite often discarded. Such words are known as stop words and need to be identified as efficiently as possible. Tokenization of text helps in identifying such words easily without much hassle. In this work, a list of Arabic stop words in [19] employed that has 750 Arabic stop words from different resources to do the stop words elimination. Figure 3 shows an example of words cloud before and after removing stop words process.

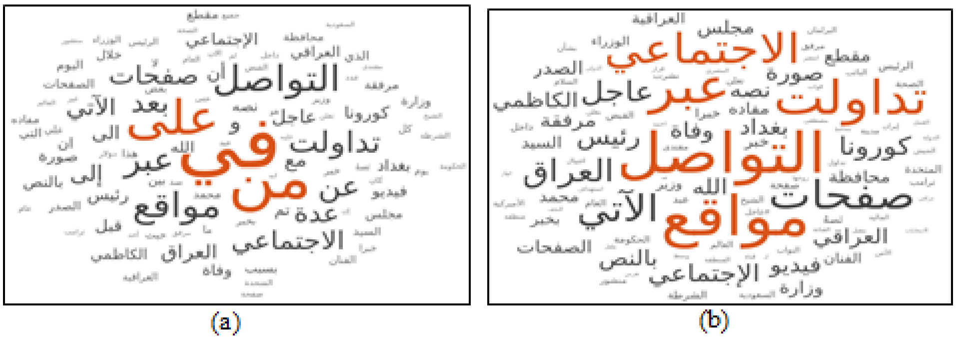

FIGURE 3. - words cloud example (a) before removing stop words (b) after removing stop words

3.3 WORD EMBEDDING

For machines to act logically and rationally, they need to be able to understand and interpret human language. This is possible with the help of Natural Language Processing (NLP) which basically is the subset of AI that deals with processing of text or sentences into machine understandable format. Text data should first be converted into numeric sequences before being input into a deep learning network. This may be done by utilizing a word encoder that converts documents into lists of numerical indices. A word embedding layer should be added to the network for improved outcomes [20, 21]. Instead of using scalar indices, word embedding's transfer words in a lexicon to numerical vectors. Words with comparable meanings have similar vectors due to this embedding's ability to capture semantic aspects of the words. Additionally, they use vector arithmetic to simulate the relationships between words.

3.4 THE CUSTOM TEXT-CNN MODEL

Figure 4 shows the Text-CNN classification model, at first, the sequence of words is input to word embedding layer of dimension (100) that maps word indices to vectors. The architecture of proposed model has two parallel paths that allow convolutions to extract more useful features from the input data. Each path contains 1D convolutional layer with number of filter of (64) followed by batch normalization, relu, dropout layer and global max-pooling layers. The output of two paths merged with each other in concatenation layer that followed by fully connected layer with two neurons, softmax and classification layer that gave the final result (fake or real) news.

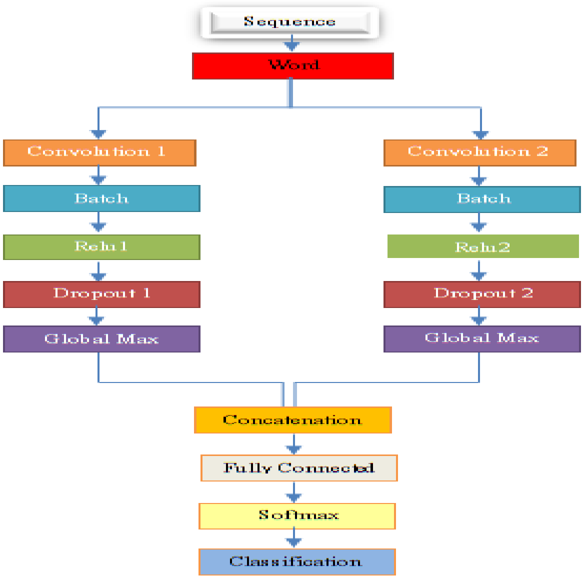

FIGURE 4. Text-CNN classification model

4. EXPERIMENTAL RESULTS

To increase the efficacy of the suggested deep learning model, several experiments have been conducted. Matlab Mathworks 2023a was used for all experiments. As part of the process of perfecting the proposed Text CNNs Arabic fake news detector, a variety of optimizers have been tested. The SGDM optimizer, ADAM, and RMSprop were all tested. For the initial learning rate, 0.01 initial learning rates has been used in this work, which is one of several well-known values from earlier false news detection codes for English text. The maximum number of epochs and the minimum batch size were set to 30 and 128 respectively, during the training phase. Table 4 shows a summary of the used parameters.

Table 4. - Common parameters

Parameter	Value
Optimizer	SGDM, ADAM and RMSprop
Epoch	30
Batch size	128
learning rate	0.01
drop	0/0.2/0.5
Data split	70% training 10%validation and 20% testing

4.1 EVALUATION METRICS

The performance of our model has been reported using weighted standard classification metrics, including F1-score, accuracy, recall, and precision. Numerous metrics may be obtained from the confusion matrix. True-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN) are the four representations of the binary classification confusion matrix.

- Accuracy is the most often used assessment metric; it determines the effectiveness of the classifier by measuring the proportion of accurate ("true") outcomes achieved by the classifier in all cases. Accuracy defines as [22]:

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

- Recall is the measure of "true positive over the count of actual positive outcomes". The formula for recall can be expressed as [22]:

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

- Precision is the measure of "true positives over the number of total positives predicted by your model". The formula for precision can be written as [22]:

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

- The F1 score is "the harmonic mean between precision and recall". The formula for the F1 score can be expressed as [22]:

$$F1\ score = \frac{2\ (precision * recall)}{(precision + recall)} \quad (4)$$

The optimal value of accuracy, recall, precision, and F1-score is 1, while their worst performance value is 0. Additionally, the best model is not only the one with the highest F1-score and accuracy, but also the one with a good balance between precision and recall.

4.2 IMPACT OF INPUT SEQUENCE SIZE IN THE PROPOSED MODEL

One of the decisions that the designer of text classification model architecture must take corresponding to input size, because it's not default hyperparameter and it can affect the performance of the classifier as well as limit the depth of network. The maximum length of each article in translated dataset (Dataset1) has been identified based on histogram of the document lengths as shown in Figure 5.

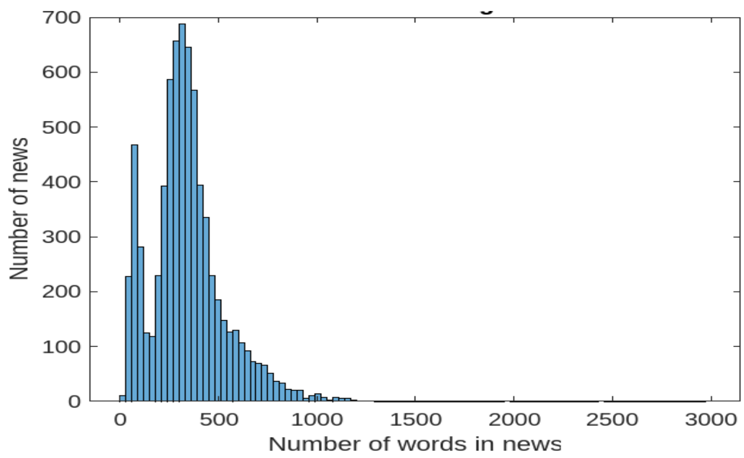

FIGURE 5. - Histogram of the document lengths in Dataset1

To guarantee that the network receives a constant length of all articles, it's necessary to determine the target length for truncation and padding. Following that, the idea of truncating was applied to each item that was longer than the target length of words, and similarly, padding with zeros was done for articles that were less than the target length of words. Three target length sizes: 250, 500, and 750 were specifically examined. For this experiment, Adam was chosen as the optimizer and dropout was set at 0.5. Figure 6 displays the findings in terms of accuracy, recall, precision, and F1-score, where it is evident that the performance of the classifier strongly depends on the length of the input sequence. The model functions most effectively with a (500) input sequence size, per the experiments that were done.

In the same context, the histogram of the document lengths of each article in Arabic dataset (Dataset2) has been used to detect the maximum length of input sequence as shown in Figure 7. From the figure, it's clear that the most of the documents have fewer than 30 words. For detect the target length that gave us best results, 20, 30 and 40 input sequence size have been used for all articles from Dataset2. Figure 8 shows the results in terms of accuracy, recall, precision, and F1-score. According to the tests performed, the model works best in Arabic dataset (Dataset2) with a (30) input sequence size.

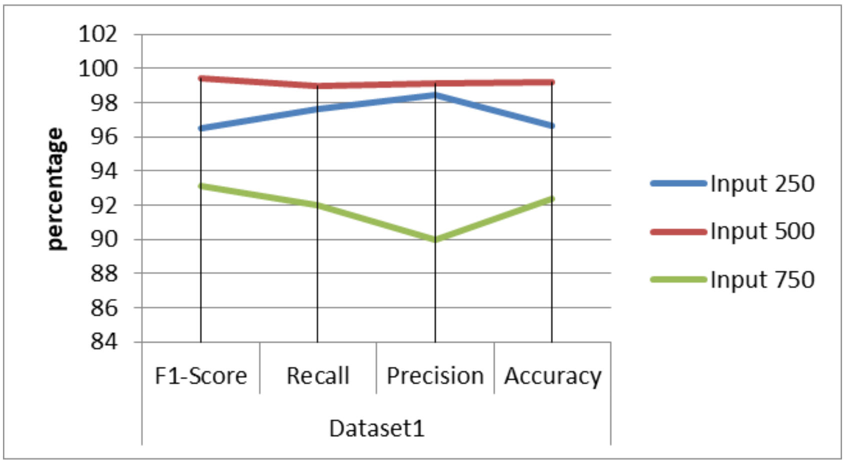

FIGURE 6. - Performance results for different target length sizes Dataset1

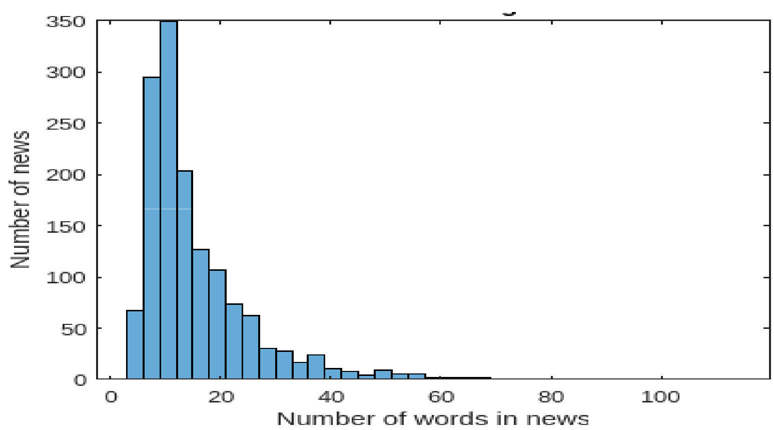

FIGURE 7. - Histogram of the document lengths in Dataset2

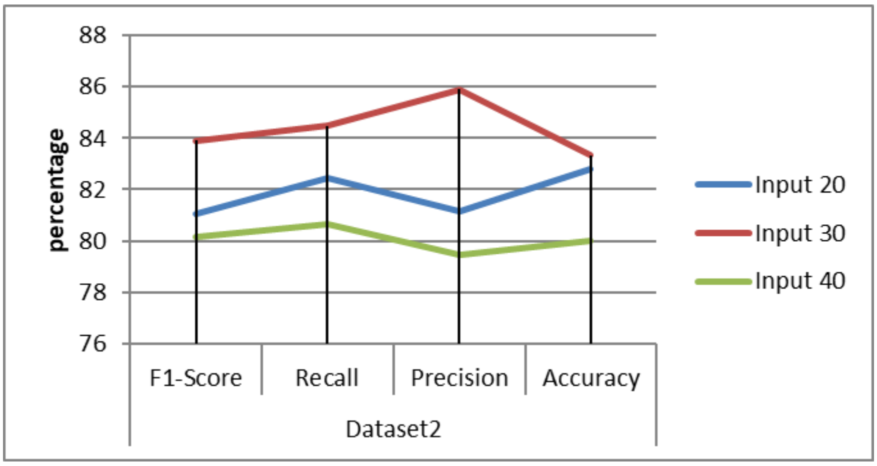

FIGURE 8. - Performance results for different target length sizes Dataset2

Based above results, it's clear that the performance results for our proposed model with Dataset1 are much better than Dataset2. The main reason for that is the Dataset2 is small and the news in it also has few numbers of words that made the proposed model not have the suitable conditions to have a good learning operation.

4.3. IMPACT OF THE DROPOUT VALUE IN THE PROPOSED MODEL

Dropout is a regularization technique used to lessen the learning model's complexity and avoid over-fitting. To assess the effectiveness of our suggested model, the dropout approach was used. In light of this, the Adam optimizer was chosen, and various dropout rates (0, 0.2, and 0.5) were applied to our network throughout our tests. The input sequence size for Dataset1 is 500 and for Dataset2 are 30. Figure 9 presents the results of this experiment done on both Dataset1 and Dataset2. In this test, the best results in all performance metrics was obtained with 0.5 dropout value.

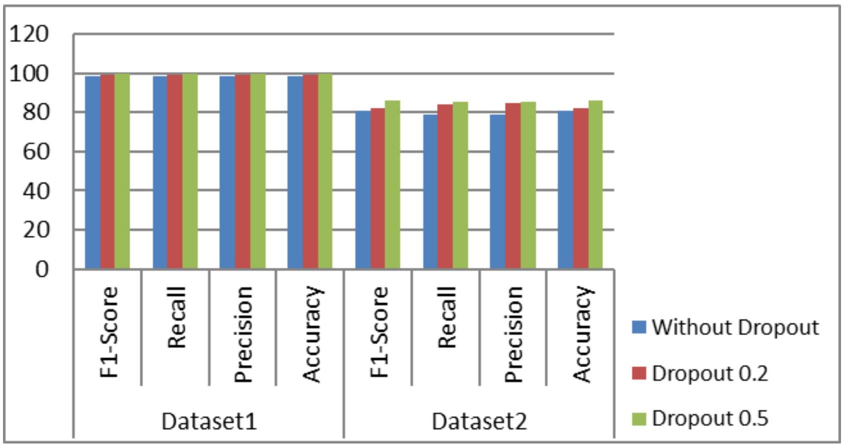

FIGURE 9. - Performance results with different dropout values

4.4. IMPACT OF THE OPTIMIZER IN THE PROPOSED MODEL

Three different optimizers were used in the proposed model's training operation. The input sequence size for Dataset1 is 500 and for Dataset2 is 30, with the learning rate fixed at the default value (0.01) and dropout value is also fixed at 0.5. Figure 10 displays the test's outcomes. Performance of SGDM and RMSProp was closer for each other, whereas Adam optimizer achieved the better performance.

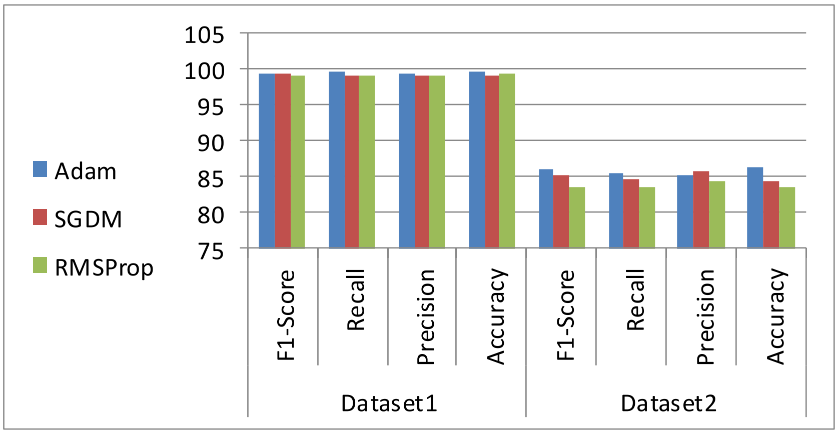

FIGURE 10. - Performance results with different optimizers

4.5. RESULTS COMPARISON

Comparing the suggested model to earlier research is important in order to demonstrate its efficacy. Experimentally compared have been done using the proposed method classification performance with some related works for Arabic-language data. All testing results are shown in Table 5.

Table 5. - Results comparison with previous works

Ref.	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Dataset size
[10]	87.8	59	39	47	8.7K
[11]	95.35	92.77	83.12	-	4K
[12]	86.6	-	-	-	6.5K
[13]	76.12	-	-	70.06	12K
[14]	91	-	-	89.9	10K
Our Dataset1	86.2	85.12	85.55	86	2K
Our Dataset2	99.67	99.45	99.65	99.5	10K

In the comparison with previous works, did not place a premium on accuracy scores. Because the datasets are not identical, comparing them using this metric is meaningless. However, when it comes to a specific evaluation metric, the F1 score has been shown to be more appropriate than the other evaluation metrics. When employing DL approaches with the proper assessment measures, the study's findings on the detection of Arabic false news were more satisfying, solid, and confident.

5. CONCLUSION

Fake news detection has received increasing attention in recent years, because of its rapid spread and negative effects. Arabic fake news detection is limited but it is a promising research field due to the lack of studies in this field. Detecting fake news in Arabic languages has several challenges such as a multiplicity of dialects, orthographic rules, rich vocabulary, and the lack of availability of Arabic data sets. In this paper, an approach for detecting fake news in the Arabic language has been proposed for detecting whether Arabic news is real or fake. Due to the limitation of the dataset in this field, English dataset has been translated to Arabic language and used another available Arabic dataset for check the proposed system performance. The results in Figures 6 and 8 show how the length of the news influences the accuracy results of model with 500 words for Dataset1 and 30 words for Dataset2 yielding the best results in terms of accuracy, precision, recall, and F1-score. Furthermore, in Figure 9, the study explored the effect of different dropout rates on model performance. A dropout rate of 0.5 was found to be the most effective across datasets, striking a balance between complexity reductions and maintaining sufficient model capacity to learn from the training data effectively. The experimental results in Table 5 show in general that the proposed Text-CNN model that based on 1D CNN outperformed the previous state of art models. For future work, increase Arabic fake news datasets is needed for training and testing with enter different Arabic dialects into the datasets.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

REFERENCES

[1] Himdi, Hanen, George Weir, Fatmah Assiri, and Hassanin Al-Barhamtoshy. " Arabic fake news detection based on textual analysis " Arabian Journal for Science and Engineering 47, no. 8 (2022): 10453-10469.

[2] Conroy, Nadia K., Victoria L. Rubin, and Yimin Chen. "Automatic deception detection: Methods for finding fake news." Proceedings of the association for information science and technology 52, no. 1 (2015): 1-4.

[3] Al-Yahya, Maha, Hend Al-Khalifa, Heyam Al-Baity, Duaa AlSaeed, and Amr Essam. "Arabic fake news detection: comparative study of neural networks and transformer-based approaches." Complexity 2021 (2021): 1-10.

[4] Agarwal, Vasu, H. Parveen Sultana, Srijan Malhotra, and Amitrajit Sarkar. "Analysis of classifiers for fake news detection." Procedia Computer Science 165 (2019): 377-383.

[5] Y. Peng, Z. Zhang, X. Wang, L. Yang and L. Lu, "Chapter 5-text mining and deep learning for disease classification, " in The Elsevier and MICCAI Society Book Series, Handbook of Medical Image Computing and Computer Assisted Intervention, Academic Press, 2020.

[6] Fouad, Khaled M., Sahar F. Sabbeh, and Walaa Medhat. "Arabic Fake News Detection Using Deep Learning." Computers, Materials & Continua 71, no. 2 (2022).

[7] Mahlous, Ahmed Redha, and Ali Al-Laith. "Fake news detection in Arabic tweets during the COVID-19 pandemic." International Journal of Advanced Computer Science and Applications 12, no. 6 (2021): 778-788.

[8] Nassif, Ali Bou, Ashraf Elnagar, Omar Elgendy, and Yaman Afadar. "Arabic fake news detection based on deep contextualized embedding models." Neural Computing and Applications 34, no. 18 (2022): 16019-16032.

[9] Jaradat, Israa, Pepa Gencheva, Alberto Barrón-Cedeño, Lluís Màrquez, and Preslav Nakov. "ClaimRank: Detecting check-worthy claims in Arabic and English." arXiv preprint arXiv:1804.07587 (2018).

[10] Alqurashi, Sarah, Btool Hamoui, Abdulaziz Alashaikh, Ahmad Alhindi, and Eisa Alanazi. "Eating garlic prevents COVID-19 infection: Detecting misinformation on the Arabic content of Twitter." arXiv preprint arXiv:2101.05626 (2021).

[11] Alkhair, Maysoon, Karima Meftouh, Kamel Smaïli, and Nouha Othman. "An arabic corpus of fake news: Collection, analysis and classification." In Arabic Language Processing: From Theory to Practice: 7th International Conference, ICALP 2019, Nancy, France, October 16–17, 2019, Proceedings 7, pp. 292-302. Springer International Publishing, 2019.

[12] Aljwari, Fatima, Wahaj Alkaberi, Areej Alshutayri, Eman Aldhahri, Nahla Aljojo, and Omar Abouola. "Multi-scale Machine Learning Prediction of the Spread of Arabic Online Fake News." Postmodern Openings 13, no. 1 Sup1 (2022): 01-14.

[13] Nagoudi, El Moatez Billah, AbdelRahim Elmadany, Muhammad Abdul-Mageed, Tariq Alhindi, and Hasan Cavusoglu. "Machine generation and detection of Arabic manipulated and fake news." arXiv preprint arXiv:2011.03092 (2020).

[14] Harrag, Fouzi, and Mohamed Khalil Djahli. "Arabic fake news detection: A fact checking based deep learning approach." Transactions on Asian and Low-Resource Language Information Processing 21, no. 4 (2022): 1-34.

[15] Alyoubi, Shatha, Manal Kalkatawi, and Felwa Abukhodair. "The Detection of Fake News in Arabic Tweets Using Deep Learning." Applied Sciences 13, no. 14 (2023)

[16] Awajan, Albara. "Enhancing Arabic fake news detection for twitters social media platform using shallow learning techniques." journal of theoretical and applied information technology 101, no. 5 (2023).
[17] Clément Bisaillon, "Fake and real news dataset." Online available at https://www.kaggle.com/datasets/clmentbisaillon/fake-and-real-news-dataset
[18] Mina Alhashimi, " Arabic Fake and Real news on facebook." Online available at https://www.kaggle.com/datasets/minaalhashimi/arabic-fake-news-and-real-on-facebook
[19] Mohamed Taher Alrefaie, "arabic-stop-words." Online available at https://github.com/mohataher/arabic-stop-words
[20] Novotný, Vít, Eniafe Festus Ayetiran, Michal Štefánik, and Petr Sojka. "Text classification with word embedding regularization and soft similarity measure." arXiv preprint arXiv:2003.05019 (2020).
[21] Li, Saihan, and Bing Gong. "Word embedding and text classification based on deep learning methods." In MATEC Web of Conferences, vol. 336, p. 06022. EDP Sciences, 2021.
[22] Costa, Eduardo P., Ana C. Lorena, André CPLF Carvalho, and Alex A. Freitas. "A review of performance evaluation measures for hierarchical classifiers." In Evaluation methods for machine learning II: papers from the AAAI-2007 Workshop, AAAI Technical Report WS-07-05, pp. 1-6. AAAI Press, 2007.
[23] Alqudsi, A., Omar, N., & Shaker, K. (2019, May). A hybrid rules and statistical method for Arabic to English machine translation. In 2019 2nd International Conference on Computer Applications & Information Security (ICCAIS) (pp. 1-7). IEEE.
[24] Hameed, M. A. A. A., Shaker, K., & Khalaf, H. A. (2023, January). Sentiment Classification of Drug Reviews Using Machine Learning Techniques. In 2023 15th International Conference on Developments in eSystems Engineering (DeSE) (pp. 457-462). IEEE.
[25] Hatem, A., Omar, N., & Shaker, K. (2011, June). Morphological analysis for rule based machine translation. In 2011 International Conference on Semantic Technology and Information Retrieval (pp. 260-263). IEEE.