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Proposed Deep Learning Model for Rumour Detection in Facebook Posts in Arabic Language

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Abstract
The emergence of Social Network Sites (SNSs) has led the individuals in general to find easy way for rapid communication with each other at any time and place. Information that spread out through (SNSs) can include a lot of unreal allegations, in which rumours and fake news on some specific manner can proliferate readily causing to a vast amount of problems. This paper addressed in order to detect the rumour posts in Facebook social site in Arabic language. The proposed work mainly relies on using sentiment analysis in order to prepare the data for extracting useful features. The Deep Convolutional Neural Network (CNN) classification model is proposed and adopted in order to perform classification operation for the extracted features from the Arabic posts. The experiential results were magnificent in which all of accuracy, precision, f-measure, and recall were equal to100%.

Keywords: Text Mining, Sentiment analysis (SA), Rumours detection, Feature Extraction, Classification, Deep Learning (DL).

1. Introduction

The (SNSs) have readily obtain a very popular place in the real life, like Facebook, Twitter, and Myspace and develop a vast number of bases belonging to a specific user in the midst decade of the century of twenty-first [1]. The most media attention goes towards the SSNs due to their fast rebound, and large user base, mainly, between the younger individuals. In general, the (SNSs) are services of Web-based that give the ability to build a profile belonging to user and make it public within a list of users with whose to share interactions, view, and carry out the connections along with the system [2]. Rumours are realized as unproven and effectively related information statements in deliberation, that appear in ambiguity form, hazard or threat [3]. The quick propagation of utilizing the SNSs resulted in dissemination of information in a minimum period of time, mostly not matched by main media causing misinformation and unverified claims (rumours) propagation through social networks in quick manner. This is increased by the fact that all users can publish false information, and it is arduous to determine the beginning source of the information [4]. Mainly, modern culture adopted the text as the most popular vehicle for the formal interchange of information. Text mining is a thriving new domain, that operate by finding out an information that is meaningful from the text of public language, in a simple manner can be introduced as a process of extracting information that is beneficial for a specific reason by performing text analysis. mainly, the text data is unstructured, amorphous, and difficult to deal with algorithmically [5]. The Complexity of natural language is main challenging issue in text mining, and machine learning algorithms are widely applied in classification but still have some limitations like in accuracy, and speed. Deep Neural Networks (DNNs) approved its power as a prevailing technique in the domain of machine learning, and provide a high performance on a multiple kinds of tasks like in recognition, regression, classification, discovery of knowledge, and so on, due to the powerful attitude that provide in dealing with a vast amount of data, and handle all kinds in a successful manner [6].

2. Related Work

Multiple researchers observed the unique behaviour of the deep learning network, and its ability in performing diagnosing and classification of the text data and determine the kind of it (rumours, real, hate speech, threats), and some of these works will be review in this section. Nguyen TN, et al. [7] in 2017, introduces an early detection method for rumour, by learning the CNNs for the unobserved illustrations of tweets rumour, and provide an enhance classification attitude equal to 91% in the first 48 hours. H, et al. [8] in 2018, provide a hierarchical network combined with features of handcrafted social depending on to three semantic levels. The LSTM network is adopted, and show 94.3% and 84.4% for the Weibo dataset and Twitter dataset. Liu Y, et al. [9] in 2018, give a model for detection the forge news by classifying the spreading paths that combine recurrent and convolutional networks, that give accuracy equal to 85% and 92% on Twitter and SinaWeibo. Bian T, et al. [10] in 2020, presented a novel model known as Bi-Directional Graph Convolutional Networks (Bi-GCN). Three dataset were employed including Weibo, Twitter15, and Twitter16 and attain accuracy results equal to 96%, 89%, and 84% in sequence. Gao J et al. [11] in 2020, propose a novel architecture of hybrid neural network, that merge task-specific character-based bidirectional language model and stacked (LSTM), and give a detection of unnoticed rumours on big augmented data of more than 12 events and 2,967 rumours within accuracy equal to 68%. Alsaeedi A, et al. [12] in 2020, illustrate a deep learning model depending on a Conventional Neural Network (CNN) to reveal pervasion of rumours on Twitter. The system is tested depending on four measures and provide accuracy equal to 87%. Asghar, M.Z, et al. [13] in 2021, a different DL models with assurance on taking into account the contextual information has been explored, and mainly based on Bidirectional LSTM with CNN, to classify the tweet into rumours and non with 86.12% accuracy. Suthanthira Devi P, et al. [14] in 2022, provide a novel NN named as Veracity Detection Neural Network for determining the rumour-linked Twitter posts' tenor in real-time circumstances, and give 90.56%, 86.18% and 93.89% accuracy of classifying the tweets into rumour or non for the PHEME dataset.

3. Methodology

The design and the implementation of the presented methodology in order to classify the Facebook posts should be performed in careful manner. In this work the Arabic posts are classified as rumours or real after performing some important steps including; data collection, separation, pre-processing that obtained using sentiment analysis, feature extraction, and finally classification as illustrated in figure 1.

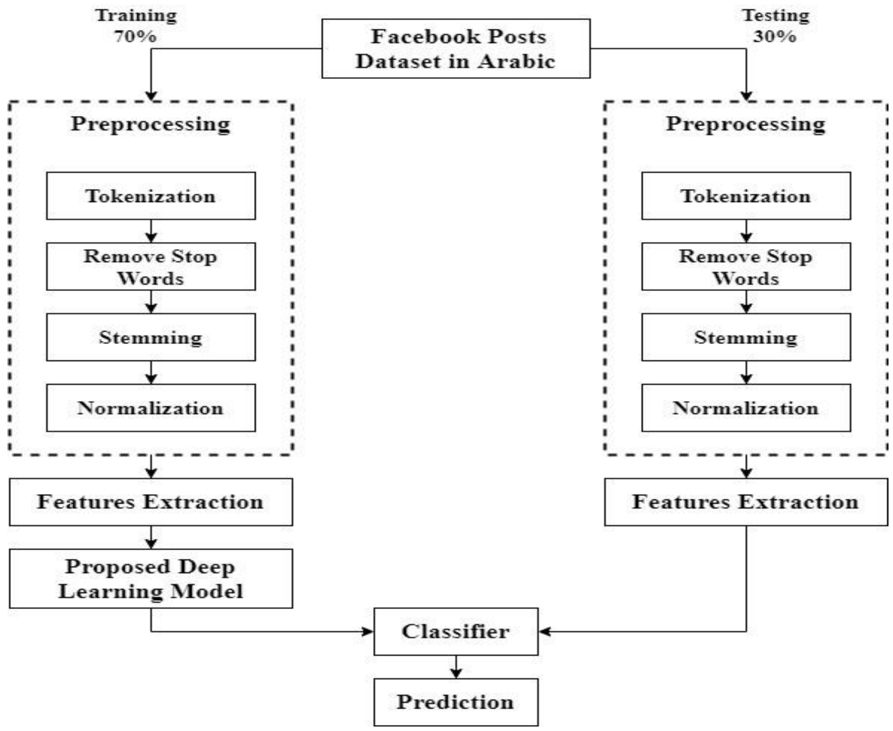

Figure 1. The proposed system block diagram

As shown in figure 1, the collected Arabic posts from the Facebook site are separated into two sets: training, and testing, and after word a pre-processing operation are implemented in order to enhance the text data before performing feature extraction. The last stage is the classification that performed using a proposed deep model.

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3.1 Dataset Collection

utilized dataset is collected from the posts of the individuals on the public posts in the Facebook web site. In which, the collection procedure is performed at first by signing into the Facebook website using phone number or email address, and afterward creating a personal page that contain the main information required in Facebook site. After finishing signing up the searching about trusted and must popular pages that have a high range to look for posts in Arabic language. The collected Arabic posts composed of 2000 posts written in Arabic, 1000 posts are real, and the other 1000 are rumours.

3.2 Pre-processing

It is the second step of the system after dividing the dataset into two groups. It pre-processes posts content to get rid of irrelevant words in, because the original dataset or raw posts are not in the optimal format. Thus, they should be pre-processed in order to clean their contents from the noise and inappropriate information. A set of procedures are performed in this step including:

- **Tokenization**

The tokens will be isolated based on line bar, punctuation symbols, and whitespaces [15]. The post text will be separated to tokens and every word will be separated from another, and in this work tokenization is performed by dividing the text into words based on spaces between them.

- **Stop words Removal**

The Stop words are referred to the words that are considerably appear, and can be realized as any word, that do not have a significance in the classification operation [16].

Table 1. examples of Arabic stop words and their English translation

English	Arabic	English	Arabic	English	Arabic
you	أنتِ	yes	بلى	he	هو
if	ان	which	اي	she	هي
yes	نعم	no	كلا	in	في

- **Stemming**

Unlike the English stemming the Arabic stemming is own a direct rule, that are easily adopted, in which the Arabic language have a complicated form, with multiple, infixes, suffixes, and prefixes that are hard to tear out. In this work the (Information Science Research Institutes) "ISRI Arabic stemmer" is adopted as stemming approach [17]. This stemmer utilizes a group of Patterns and Roots, and Affix of Arabic language.

- **Normalization**

In this procedure the resulted text posts are cleaned from all the unnecessary information [18]. This includes removing irrelevant information such as punctuation, symbols, special characters, numbers, username, URLs links, non-Arabic letters.

3.3 Feature Extraction based on TF-IDF

the weight of word in the intended document is determined in this method by enumerating its frequency, while in inverse appearance to the count of documents where the word conspicuous in the group of documents. TF-based elevated weight values is provided in equation (1) [19].

$$\mathbf{TF} = \boldsymbol{NW/ND} \qquad \mathbf{1}$$

Where $\boldsymbol{NW}$ is the count of appearance of word w in the document, and $\boldsymbol{ND}$ is the overall count of terms.

TF-IDF separate the local frequency of term on the frequency of the term in document, which will provide more weight to seldom used words, which will specify such words that are characteristics concerning specific author. Such as, when author head for using the word "رائع" a lot, TF/IDF will devote more weight to this word, and minimum weight to more frequent shared ones, like "هي" or "هو". Inverse document frequency for giving word w will be determined as viewed in equation (2) [20].

$$\mathbf{IDF = (N/dfw)} \qquad \mathbf{2}$$

Which N demonstrated the count of documents in frame, and dfw show documents' count that composed of word w. TF/IDF for specific word w could be calculated using equation (3) [21]:

$$\mathbf{TF - ID}\mathrm{F} = (\mathbf{TF\ w\ x\ log}\ (\mathbf{N/dfw})) \qquad \mathbf{3}$$

In general, three main steps are performed in order to extract features using this method including

a. Creating Vocabularies
b. Creating a Vector of Features
c. Computing Features Weight

3.4 Classification within a Proposed Deep CNN Neural Network

The term "neural network" refers to a collection of numerous simple, interlinked processors called neurons, each of which emits a sequence of real-valued activations [22]. A type of NN named as Conventional Neural Network (CNN), which it is deep learning network is achieved in the proposed system. Deep learning-based approaches have been successfully employed in the field of text mining and analysis in recent years. The term deep learning determined as wide class of machine learning techniques, and architectures, that have a trait of utilizing a set of wide number of layers [23]. Mainly, the proposed model composed of eleven layers including; six Convolutional layers of type 1 dimension, and five layers of ReLU activation function. The adoption of CNN of 1 dimension provide the ability to give an accurate result even if there is a little amount of data, as well the computational complexity considered to be low compared within the type of 2 dimension also the it can be implemented in a simple environment with a low cost that suits the real-world application. The Soft- Max function also adopted in the final layer of the model that perform the scores conversion into a normalized probability distribution. Figure 2, provide a description about the proposed deep model layers, as well Table 2, illustrate the architecture details of the model.

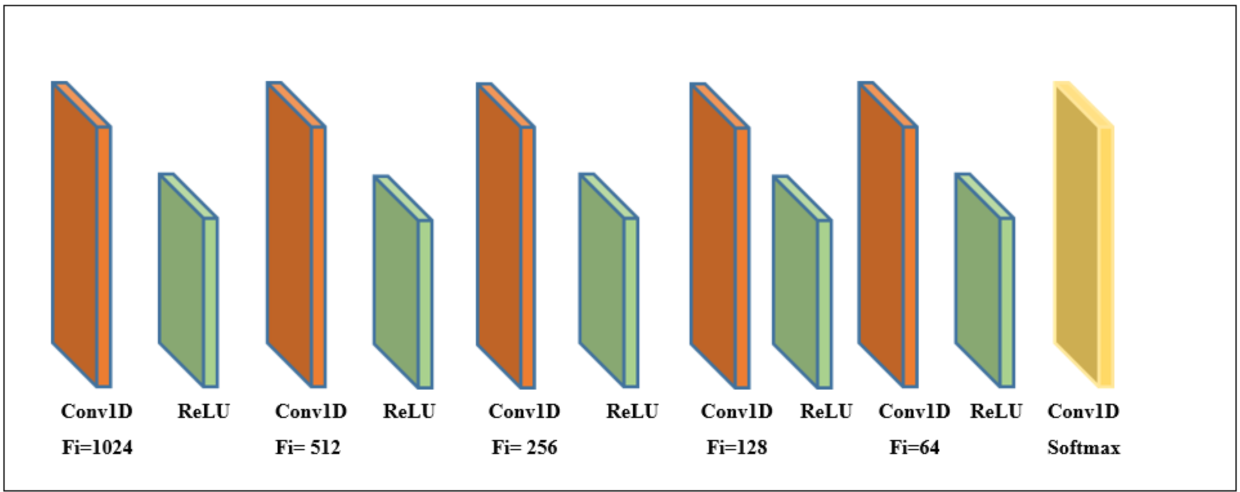

Figure 2. The proposed deep CNN model for Rumour detection

Table 2. proposed deep Model Architecture

No.	Layer Type	Parameter	Output-shape
1	Convolution 1D	2504704	(None, 1024)
2	ReLU	-	-
3	Convolution 1D	524800	(None, 512)
4	ReLU	-	-
5	Convolution 1D	131328	(None, 256)
6	ReLU	-	-
7	Convolution 1D	32896	(None, 128)

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8	ReLU	-	-
9	Convolution 1D	8256	(None, 64)
10			
11	Convolution 1D	130	(None, 2)

4. Results and Discussion

The classification and determining the post are rumours or real are performed using the presented system in this work and mainly depends on the utilized steps reaching to the most important phase which it is the classification. The proposed deep model performance is evaluated using popular metrics including; Accuracy, Precision, F-measure, and Recall. The acquired results were all magnificent, and equal to 100% percent as described in figure 3.

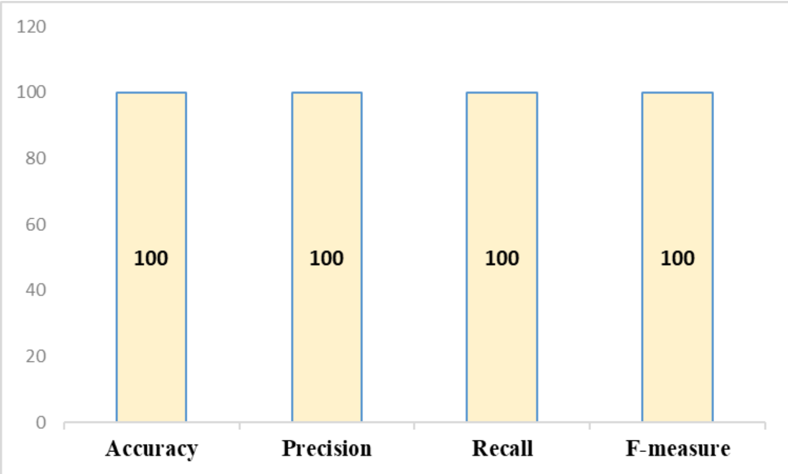

Figure 3. Experimental results of the proposed deep learning model

Figure 3, demonstrate the success of the presented model and the powerful attitude that obtained from the proposed deep model of kind one dimension. The acquired results are obtained after training the system on 3,202,114 number of parameters, within zero loss, an epoch value equal to 100 of patch size within 64 value.

5. Conclusion

There is an increased research heading towards finding and allocating rumours, due to exaggeration in utilizing the platforms of social media for broadcasting of information, and news. Many intrinsic studies have concentrated on identifying the source of the rumours and detecting it. In this work detection the rumours in Arabic language is performed depending of the usage of deep learning platform. The obtained result in classification the Facebook post and determine if the post is real or rumour has shown a great performance within the achievement of a proposed deep learning model and give an accuracy equal to 100% percent. The utilization of the sentiment analysis in order to clean the ambiguous unordered textual data, along with extraction the features before performing the final classification phase demonstrate its effect in acquiring the perfect result from the model.

References

[1]. Thelwall, Mike. "Social network sites: Users and uses." Advances in computers 76 (2009): 19-73.
[2]. Boyd, Danah M., and Nicole B. Ellison. "Social network sites: Definition, history, and scholarship." Journal of computer-mediated Communication 13, no. 1 (2007): 210-230
[3]. Einwiller, Sabine A., and Michael A. Kamins. "Rumor has it: The moderating effect of identification on rumor impact and the effectiveness of rumor refutation 1." Journal of applied social psychology 38, no. 9 (2008): 2248-2272

[4]. Seo, Eunsoo, Prasant Mohapatra, and Tarek Abdelzaher. "Identifying rumors and their sources in social networks." In Ground/air multisensor interoperability, integration, and networking for persistent ISR III, vol. 8389, pp. 417-429. SPIE, 2012.

[5]. Sumathy, K. L., and M. Chidambaram. "Text mining: concepts, applications, tools and issues-an overview." International Journal of Computer Applications 80, no. 4 (2013).

[6]. Schmidhuber, Jürgen. "Deep learning in neural networks: An overview." Neural networks 61 (2015): 85-117

[7]. Nguyen, Tu Ngoc, Cheng Li, and Claudia Niederée. "On early-stage debunking rumors on twitter: Leveraging the wisdom of weak learners." In International Conference on Social Informatics, pp. 141-158. Springer, Cham, 2017.

[8]. Guo, Han, Juan Cao, Yazi Zhang, Junbo Guo, and Jintao Li. "Rumor detection with hierarchical social attention network." In Proceedings of the 27th ACM international conference on information and knowledge management, pp. 943-951. 2018.

[9]. Liu, Yang, and Yi-Fang Wu. "Early detection of fake news on social media through propagation path classification with recurrent and convolutional networks." In Proceedings of the AAAI conference on artificial intelligence, vol. 32, no. 1. 2018.

[10]. Bian, Tian, Xi Xiao, Tingyang Xu, Peilin Zhao, Wenbing Huang, Yu Rong, and Junzhou Huang. "Rumor detection on social media with bi-directional graph convolutional networks." In Proceedings of the AAAI conference on artificial intelligence, vol. 34, no. 01, pp. 549-556. 2020.

[11]. Gao, Jie, Sooji Han, Xingyi Song, and Fabio Ciravegna. "Rp-dnn: A tweet level propagation context based deep neural networks for early rumor detection in social media." arXiv preprint arXiv:2002.12683 (2020).

[12]. Alsaeedi, Abdullah, and Mohammed Al-Sarem. "Detecting rumors on social media based on a CNN deep learning technique." Arabian Journal for Science and Engineering 45, no. 12 (2020): 10813-10844

[13]. Asghar, Muhammad Zubair, Ammara Habib, Anam Habib, Adil Khan, Rehman Ali, and Asad Khattak. "Exploring deep neural networks for rumor detection." Journal of Ambient Intelligence and Humanized Computing 12, no. 4 (2021): 4315-4333.

[14]. Suthanthira Devi, P., and S. Karthika. "Rumor Identification and Verification for Text in Social Media Content." The Computer Journal 65, no. 2 (2022): 436-455.

[15]. Cambria, Erik, and Bebo White. "Jumping NLP curves: A review of natural language processing research." IEEE Computational intelligence magazine 9, no. 2 (2014): 48-57

[16]. Sarica, Serhad, and Jianxi Luo. "Stopwords in technical language processing." Plos one 16, no. 8 (2021): e0254937

[17]. Dahab, Mohamed Y., Al Ibrahim, and Rihab Al-Mutawa. "A comparative study on Arabic stemmers." International Journal of Computer Applications 125, no. 8 (2015).

[18]. Ariffin, Siti Noor Allia Noor, and Sabrina Tiun. "Rule-based text normalization for Malay social media texts." International Journal of Advanced Computer Science and Applications 11, no. 10 (2020).

[19]. Zhang, Wen, Taketoshi Yoshida, and Xijin Tang. "A comparative study of TF* IDF, LSI and multi-words for text classification." Expert Systems with Applications 38, no. 3 (2011): 2758-2765

[20]. Qaiser, Shahzad, and Ramsha Ali. "Text mining: use of TF-IDF to examine the relevance of words to documents." International Journal of Computer Applications 181, no. 1 (2018): 25-29

[21]. S. Vijayarani, M. J. Ilamathi, and M. Nithya, "Preprocessing techniques for text mining-an overview," Int. J. Comput. Sci. Commun. Networks, vol. 5, no. 1, pp. 7–16, 2015

[22]. Goldberg, Yoav. "Neural network methods for natural language processing." Synthesis lectures on human language technologies 10, no. 1 (2017): 1-309.

[23]. Maslej-Krešňáková, Viera, Martin Sarnovský, Peter Butka, and Kristína Machová. "Comparison of deep learning models and various text pre-processing techniques for the toxic comments classification." Applied Sciences 10, no. 23 (2020): 8631.